Scared to Death?
Information Avoidance and Diagnostic Testing

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May 31, 2018

Abstract

Americans' use of preventive care is half the recommended level. In fact, greater utilization of preventive care has become a national health policy objective. Previous economic studies suggest that price is not the only important factor that impacts the demand for preventive care. In addition, empirical evidence suggests that some people are health information avoidant, which means that they prefer not knowing information about their health even when diagnostic testing is free and very accurate. To explain this puzzle, this study embodies insights from the economics theoretical literature to incorporate health anxiety, which represents the stress or disutility associated with the anticipation of bad outcomes, as another potential cost of having a test in an individual's forward-looking, dynamic decisionmaking process. With data from the Health and Retirement Study (HRS), I evaluate the roles of many contributors, including health anxiety, to the observed type-2 diabetes screening behavior by jointly estimating a set of equations derived from a forward-looking individual's decision-making optimization problem. In the model, she chooses the number of doctor visits, lifestyle behaviors, and employment; underlying disease state governs her diabetes stage and she has imperfect information about her true health. Estimation results suggest that the monetary costs, time costs, health and longevity expectations, and health anxiety are all important contributors to an individual's blood sugar testing behavior. Individuals' health-related behaviors also respond to health information associated with screening tests.

JEL Classification Numbers: I11, I12, D83

Key Words: Information avoidance, diabetes screening, health behavior

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1 Introduction

According to the Centers for Disease Control and Prevention (CDC), consumption of preventive medical care is well below recommended levels. In fact, greater utilization of preventive care, especially for chronic conditions, has become a national health policy objective (e.g., the Healthy People 2020 Leading Health Indicators). Basic economic theory suggests that a reduction in the price of preventive care will increase the amount demanded. Recent U.S. reforms embodied in the Affordable Care Act (ACA) reflect this insight by requiring that insurance companies impose no consumer cost-sharing on approved preventive services. However, economic studies that exploit the exogenous changes in cost-sharing brought about by the RAND Health Insurance Experiment and the ACA reforms suggest that something else, other than price, may have an important impact on demand for preventive services. For example, data from the RAND Health Insurance Experiment suggest that, even with zero out-of-pocket costs, the majority of adult males used no preventive care at all for three years (Newhouse et al., 1993). Using more recent data, some researchers find that reductions in the price of screening (for high cholesterol, breast cancer, diabetes, etc.) encourage its use (Finkelstein et al., 2012), while others find that consumers are not very sensitive to the price of preventive care (Newhouse et al., 1993; Simon et al., 2016; and Sabik and Bradley, 2016).

In addition to this ambiguity among results, it has been suggested that some people are health information avoidant, which means that they prefer not knowing information about their health even when the screening tests are free and very accurate (Oster et al., 2013 and Ganguly and Tasoff, 2016). This type of behavior suggests that there might be additional costs associated with having a test that are not captured by our traditional economic model. To address this puzzle, economists have adapted theoretical models of individual behaviors by incorporating anticipatory utility, which suggests that individuals acquire utility directly from expectations, or anticipations, about the future. That is, the model should consider health anxiety, which represents the stress or disutility associated with the anticipation of positive (i.e., bad outcome) test results, as an additional cost in an individual's forward-looking, dynamic decision making process (Caplin and Leahy, 2001; Kőszegi, 2003 and Caplin and Eliaz, 2003).

Although widely discussed in the economic theory literature, this concept of health anxiety remains underexplored empirically because measurement is, to date, elusive. That is, there is no validated survey measure of individual avoidance of particular preventive care screenings/testings due to anxiety about the results. Alternatively, and as I propose, this kind of behavior can be approximated and inferred using variation in particular

personality characteristics after modeling the many other potential explanations for non-participation in a recommended testing. Following the definition of health anxiety in the economic theoretical literature, an individual's pessimism level serves as a good approximation for health anxiety as people who are more pessimistic are more likely to anticipate a bad result and thus suffer from this disutility. This study evaluates the role of many contributors, including health anxiety, to type-2 diabetes screening behavior by developing a dynamic, stochastic model of an individual's decisions about doctor visits (at which a blood sugar test may or may not be administered), other health-related behaviors, and employment where underlying disease state governs diabetes stage, individuals have imperfect information about their true health (if untested), and health anxiety is approximated by an individual's pessimism level.[1] By incorporating health anxiety, this study provides a richer framework for understanding an individual's non-participation in diabetes screening.

Type-2 diabetes, or diabetes mellitus type 2, is a long-term metabolic disease characterized by a high blood sugar level over a prolonged period because the cells fail to use insulin properly to process glucose.[2] Type-2 diabetes is primarily caused by obesity and lack of exercise and commonly manifests in adulthood. The common treatments include exercise, diet adjustment, oral medication and insulin shots. Poorly-managed diabetes can progress irreversibly to severe stages and cause other complications such as blindness, lower body amputation, heart attack and stroke (Oster, 2015 and Mroz et al., 2016). Type-2 diabetes provides a good setting to study testing behavior and health anxiety for three reasons. First, the asymptomatic features of diabetes enable me to examine testing behavior and health anxiety without worrying about the confounding effects of disease symptoms on medical care consumption behavior. Second, it is often difficult to distinguish health anxiety from the disutility associated with the testing procedure itself. Diabetes screening (or the blood sugar test) is less invasive than other preventive tests such as a mammogram, prostate, or cancer screening. Third, understanding the diabetes screening behavior is of significant policy importance. Diabetes is a prevalent and growing chronic condition. There are 29 million Americans (i.e., 1 out of every 11 Americans) living with diabetes, 86 million (i.e., 1 out of every 3 Americans) living with pre-diabetes and 1.7 million new cases diagnosed each year.[3] Because diabetes is an asymptomatic

[1] In this paper, a blood sugar test refers to type-2 diabetes screening.

[2] With type-1 diabetes, a high blood sugar level results from the failure of the pancreas to produce any insulin. The cause of type-1 diabetes is not clear and it usually starts in childhood. Type-1 diabetic patients have to take a routine insulin shot as a replacement of pancreatic function. In this paper, 'diabetes' refers to type-2 diabetes.

[3] Pre-diabetes is the precursor stage of type-2 diabetes, when the blood sugar level is higher than normal but not yet high enough to be diagnosed as diabetes.

disease, preventive screening is important. According to the CDC, up to 25 percent of U.S. adults who have diabetes do not know that they have it, and 90 percent of people with prediabetes are unaware. Without any life-style changes, 15 to 30 percent of people with prediabetes will develop type-2 diabetes within five years (CDC Division of Diabetes Translation, 2014). In fact, only half of individuals for whom diabetes screening is recommended comply. Additionally, diabetes is more costly to treat if detected later (Mroz et al., 2016). Given that the annual costs of diabetes account for 20 percent of national medical care costs ($176 billion in direct medical costs and an additional $69 billion associated with reduced productivity in 2012), an improvement in diabetes screening behavior could have both individual and societal impacts (American Diabetes Association, 2013).

The impacts of various contributors on an individual's diabetes screening behavior are explicitly delineated in the theoretical model. The contributors are: monetary and time costs of doctor visits and tests; the marginal effectiveness of different types of medical and non-medical inputs for controlling blood sugar levels; an incorrect perception of health; life expectancy; and health anxiety. To reflect the fact that physicians may also play an important role in an individual's screening behavior, I assume that an undiagnosed individual, with at least one doctor visit during a two-year period, may receive a diabetes screening (or a blood sugar test) with some probability. Prior to learning her true disease state (which can only be verified with a blood sugar test), an individual bases her decisions about medical care use and other health behaviors on her perceived, or subjective, health status. The subjective and true disease states capture the degree to which information about one's own health is imperfect. Subjective beliefs about one's health are captured by self-reported health status and a subjective survival probability.

Solving the optimization problem, I derive the demand behaviors (i.e., doctor visits, employment, exercise level, smoking and excessive drinking) as a function of information available to the individual at the beginning of the period. Approximations of the demand equations yield a set of estimable equations that are jointly estimated with observed stochastic outcomes (i.e., diabetes screening and hospitalization nights), health outcomes (i.e., blood sugar level evolution, body mass accumulation, death) and expectations processes (i.e., self-perceived health status and subjective survival probability transitions). The joint estimation procedure allows for common unobservables that might influence several outcomes within a period and/or over time. Simulations based on the estimated data-generating process are used to evaluate the relative marginal contribution of each contributor, including health anxiety, to an individual's behaviors and health outcomes over a lifetime.

My primary data source is the Health and Retirement Study (HRS) survey and its

linked biomarker data. The HRS survey data are longitudinal, with biennial observations from 1992 to 2014. New cohorts enter the survey every six years. Constrained by the availability of blood sugar test information, I only use the data from 2004 to 2012. The survey provides information about an individual's employment, health-related behaviors, medical care consumption, diabetes status, and blood sugar testing behavior. The linked biomarker data collect and test respondents' blood samples biennially from 2006 to 2012, from which I can observe an individual's true disease state.

I contribute to the literature by estimating and evaluating the marginal effects of many contributors to the observed diabetes screening behavior. The estimation results suggest that monetary and time costs of doctor visits and tests, health and longevity expectations, and health anxiety are all important contributors to an individual's blood sugar testing behavior. Specifically, a health anxious individual is less likely to receive a diabetes screening test by reducing the number of doctor visits and avoiding the test during a visit. The health information associated with a diagnosis of diabetes or taking a test influences an individual's body mass production contemporaneously and lifestyle behaviors in the subsequent periods.

The rest of the paper is structured as following. Section 2 discusses the related literature, Section 3 introduces a simple theoretical model to motivate inclusion of the various contributors of screening behaviors, and Section 4 provides information about the data and estimation sample. Section 5 describes the derived empirical framework. Section 6 presents estimation results and Section 7 discusses policy simulations. Lastly, Section 8 concludes.

2 Related Literature

2.1 Preventive care is beneficial

In seminal work by Ehrlich and Becker (1972), preventive care is introduced to the medical care demand discussion (among economists) as "self-protection" and "self-insurance". In their model, there are three ways an individual can respond to health uncertainty: market insurance, self-protection and self-insurance. Self-protection encompasses primary preventive care (e.g., flu vaccine) as it can reduce the probabilities of bad health states; while self-insurance captures secondary primary care (e.g., diabetes and cancer screening) as it reduces the size of the loss in the bad states. Their theoretical model suggests that, because market insurance and self-insurance are substitutes, a moral hazard problem may arise if the price of market insurance is not negatively related to the

amount spent on protection. Some studies discuss the optimal coverage for and benefits of preventive care. Howard (2005) characterizes the theoretical relationship between age and cost-effectiveness of early detections. He claims that there is always an age beyond which the costs of early detection outweigh the benefits. However, his model assumes that individuals are risk neutral and that screening occurs every period, and it abstracts away from psychological factors. Herring (2010) claims that the enrollee turnover among health insurers explains the suboptimal provision of coverage of preventive health care: the financial benefits of preventive care accrue in the future and some of the benefits to an insurer will be lost when the enrollees change health plans. Mroz et al. (2016) provide empirical evidence that screening tests and early diagnoses of type-2 diabetes are beneficial. They estimate a dynamic multistage duration model that includes partial observability of the disease stage, unmeasured heterogeneity, and the endogenous timing of diabetes screening. The results indicate that earlier diagnosis of diabetes delays the onset of lower extremity complications (LECs) and amputation. For example, a one year delay in the diagnosis of diabetes increases the probability that an individual will have LECs five years later by 11 percent and the probability of transition to high severity LECs by 27 percent. Furthermore, their policy simulation estimates that if Medicare were to cover no more than two visits per year for healthy individuals, over a 15-year span it would save Medicare $476 per beneficiary at a cost of only 0.004 years of life per person. Preventive testing can have negative externalities. For example, Oster et al. (2010) find empirical evidence of adverse selection in the long-term care insurance market due to increased private information by genetic testing.

2.2 Demand for preventive testing

Most studies find that health insurance coverage increases the utilization of preventive care. Finkelstein et al. (2012) explore the exogenous cost shock of the Oregon Medicaid lottery and find that insurance is associated with a significant and large increase in compliance with recommended preventive care: 20 (15) percent increase in the probability of ever having blood cholesterol (sugar) checked, and 60 (45) percent increase in the probability of having a mammogram (pap test) within the past year. Sabik and Bradley (2016) employ a quasi-experiment framework to analyze the effect of the expansion to near-universal health insurance coverage in Massachusetts on breast and cervical cancer screening. They find a significant but mild increase in the screening rates: a 4 to 5 percent increase in mammogram and a 6 to 7 percent increase in pap tests annually. Even with near-universal health insurance, the testing rates are not close to universal: 77.8 percent for mammogram and 75.1 percent for pap test annually. Newhouse et al. (1993)

examine the RAND Health Insurance Experiment and find that consumers are not very sensitive to price of preventive care: the price elasticity of demand for preventive care is in the range of -0.17 to -0.43. Simon et al. (2016) explore the 2014 Affordable Care Act (ACA) Medicaid expansions and find mixed effects on a variety of preventive care behaviors. There is an increased use of dental visits, mammogram, and cancer screening, but no detectable change for flu shots, HIV tests, or pap tests. Pagán et al. (2007) also find that uninsured adults are less likely to undertake screening for high cholesterol and diabetes in Mexico.

Besides health insurance coverage, some other factors also influence the demand for preventive testing, such as availability of treatment, information, and disutility from the test. Okeke et al. (2013) conduct a field experiment in Nigeria and find that women who randomly receive a cervical cancer treatment subsidy are 4 percentage points more likely to take up the screening test. Bíró (2013) analyzes the breast cancer screening behavior of women aged 50-64 in the UK. She models the screening decision as an inter-temporal decision about whether to attend a due screening in a 3-year period and considers three factors influencing the screening attendance: the disutility of screening, the effect of screening on survival probability, and the discount factor. The results indicate forward-looking behavior, but education differences in mammography attendance are mainly due to lower disutilty of screening among higher educated women rather than different time preferences. Carrieri and Bilger (2013) investigate the under-usage of preventive care in Italy and find that general practitioners play a minor role, while non-monetary barriers (i.e., geographic and organizational barriers) and health beliefs and knowledge are strong determinants. The effect of information is ambiguous. Jacobsen and Jacobsen (2011) evaluate the effect of National Breast Cancer Awareness Month (NBCAM) on breast screening behavior. They find that the NBCAM has significant and positive effects on diagnosis of breast cancer, which is used as a proxy for screening behavior. Rapp (2014) finds that the presence of Alzheimer's disease in the family, which provides good information about the disease, actually slows diagnosis of Alzheimer's disease.

2.3 Some people are information avoidant

There is some empirical evidence to indicate that people are health information avoidant, which means that they do not take the screening tests even when the tests are free and very accurate. Facione (1993) discovers that 34 percent of women with breast cancer symptoms delay seeking help for three or more months. Even more puzzling is the evidence that patients who seem to have more to gain from visiting the doctor are sometimes less likely to go. Caplan (1994) reports that women whose breast cancer symptoms are getting

worse delay longer in seeing a professional than those whose symptoms are steady or disappearing. Lerman et al. (1996) find that 40 percent of high-risk patients who are offered a test for genetic susceptibility to breast and ovarian cancer declined the test. A similar study by Lerman et al. (2004) on a type of colon cancer discovers that 57 percent of high-risk individuals declined to test. Thornton (2008) conducts an experiment in rural Malawi and finds that only 34 percent of the participants without a monetary incentive learned their HIV results. Inspired by the empirical evidence, some studies have begun to focus on health anxiety in particular. A recent behavioral experiment by Ganguly and Tasoff (2016) finds evidence of health anxiety. Among college students who have already had blood collected, those who do not want to know if they have a Sexually Transmitted Disease (STD) must pay $10 to avoid having their blood tested. Results show that 15 percent of students are willing to pay to avoid the test and the top reason is that "it will cause me unnecessary stress or anxiety if I test positive". Wu (2003), using the HRS and MEPS data, finds that self-reported health status is positively and significantly associated with having a flu shot, but negatively associated with having a pap smear, breast exam, mammogram and prostate check. The negative correlation between health status and screening tests may be due to fear or anxiety associated with learning health information because those who are more pessimistic are less likely to do those tests.

2.4 Literature with belief-dependent utility

This study is also closely related to a growing amount of theoretical literature that incorporates behavioral and emotional factors using belief-dependent utility. It is common in modern economics to assume that humans have unlimited cognitive ability to make optimal decisions. Thus, the value of information exactly equals the extent to which it improves decisionmaking and it cannot be negative (Bénabou and Tirole, 2016). However, often times, human decisionmaking involves a combination of emotions and limited cognitive ability. As Schelling (1988) describes, the mind is a consuming organ. Information may have both instrumental and direct value through belief-dependent utility and, therefore, lead to information avoidance. Bénabou and Tirole (2016), Gino et al. (2016), and Epley and Gilovich (2016) provide good summaries and explanations about motivated belief and reasoning. They emphasize that beliefs often contain important psychological value. Thus, people tend to manipulate their collection and processing of information in ways that depart from strict Bayesian inference, trading off the affective value of belief distortion against the costly mistakes they may induce.

The motivation for motivated belief is twofold. First, belief has instrumental value; for example, an individual prefers to hold a distorted belief to solve a self-control problem.

Second, belief can have direct utility through anticipatory utility, which means agents' experience feelings of anticipation prior to the resolution of uncertainty into utility (Caplin and Leahy, 2001). Motivated belief can be formed by motivated collection (e.g., attorneys collect evidence to support their own side), motivated avoidance (e.g., heath anxiety prevents people from taking tests), reality denial, and self-signaling. Golman et al. (2016) provide a summary of explanations for information avoidance. They categorize the reasons into two types: hedonically-driven information avoidance, which includes reasons such as anxiety, optimism maintenance, and belief investment; and strategically-driven information avoidance, which includes resisting temptation, motivation maintenance, save it for later, etc. Karlsson et al. (2009) model the ostrich effect, which means that individuals regulate the impact of good and bad news on their utility by how intently they attend to the news. They use the fact that investors are less likely to check their portfolios in down and flat markets than in up markets as empirical evidence of the ostrich effect.

Some studies apply these theoretical models and focus on patient behavior. Kőszegi (2003) extends the Caplin and Leahy (2001) model to analyze health anxiety and patient behavior. The main idea is that people can be "information averse" or "information loving" depending on the shape of their utility functions. An information averse patient prefers not to see a doctor, even at the cost of better treatment with accurate information. His model implies that health anxiety is more likely to keep patients away from seeking help in more serious cases. Oster et al. (2013) explore the decision to undergo genetic testing for Huntington Disease. In their sample, fewer than 10 percent of individuals at risk for the disease actually pursue predictive testing during the 10-year study period. Furthermore, they find that individuals who are uncertain always behave identically to those who are not carriers of the disease gene. They suggest an optimal expectation model (Brunnermeier and Parker, 2005), in which individuals get utility directly from beliefs about the future and can manipulate their beliefs if not tested, to explain the behaviors. Caplin and Eliaz (2003) develop a theoretical model that embodies health anxiety as an additional cost of taking an AIDS test and design a mechanism to improve testing and slow the spread of the disease. Fang and Wang (2015) extend the semiparametric estimation method for a discrete choice model to the setting of hyperbolic discounting time preference. Empirically, they find evidence for both present bias and naivety for the mammography screening.

3 Theoretical Motivation

Before presenting a detailed dynamic stochastic model, I use a 2-period model to describe the demand for diagnostic testing in a simplified environment.

3.1 Model setup

Consider a two-period game. At $t = 0$, nature moves to decide an individual's state of the world $s \in \{0, 1\}$, where $s = 1$ indicates that the individual has diabetes and $s = 0$ indicates she does not. The decision maker then evaluates her payoffs and chooses her behaviors (actions). I describe the components of decisionmaking here.

(1) Information: the decision maker does not observe her true state, s, of the world, but holds a belief $\pi = E[s]$ that represents her subjective probability of having diabetes.

(2) Actions:

- A binary screening test choice ($b \in \{0, 1\}$) at $t = 0$. If a diabetes screening is performed ($b = 1$), the individual knows her true state of the world. Furthermore, if she is diagnosed, she can receive treatment M; otherwise she does not know the state of the world and cannot receive any treatment.

- A binary lifestyle action ($a \in \{0, 1\}$) at $t = 1$. The action $a = 1$ indicates a very healthy lifestyle (e.g., more exercise, no smoking, no binge drinking, and sugar-less diet) and $a = 0$ indicates normal or usual lifestyle.

(3) Payoffs: payoff $u(s, a)$ is realized at $t = 2$ where

$$\begin{cases} u(0,0) = 1 & \text{no diabetes, normal lifestyle} \\ u(0,1) = 1 - \Phi & \text{no diabetes, very healthy lifestyle} \\ u(1,0) = -\Omega & \text{with diabetes, normal lifestyle} \\ u(1,1) = 0 & \text{with diabetes, very healthy lifestyle} \end{cases}$$

I normalize the utility from matched lifestyle choice and the true state of world and assume Φ, Ω and M all lie within [0,1]. That is, the utility of "no diabetes, normal lifestyle" and "with diabetes, very healthy lifestyle" are normalized to be 1 and 0, respectively; and the utility from a mismatched lifestyle choice is lower than the matched one. There is a monetary (and time) cost, c, of taking a screening test.

Lemma 1: If the individual chooses not to test ($b = 0$), her optimal lifestyle choice (a) is:

$$\begin{cases} a^* = 0 & \text{if } \pi < \frac{\Phi}{\Omega+\Phi} \\ a^* = 1 & \text{if } \pi \geq \frac{\Phi}{\Omega+\Phi} \end{cases}$$

(The proof is shown in Appendix A.)

Let a^* be the optimal lifestyle given π as shown in Lemma 1. Therefore, the expected value of not taking a test, $V^b(\pi)$ where $b = 0$, is:

$$\begin{aligned} V^0(\pi) &= \pi u(1, a^*) + (1-\pi)u(0, a^*) \\ &= \begin{cases} 1 - \pi(1+\Omega) & \text{if } \pi < \frac{\Phi}{\Omega+\Phi} \\ (1-\pi)(1-\Phi) & \text{if } \pi \geq \frac{\Phi}{\Omega+\Phi} \end{cases} \end{aligned} \tag{1}$$

I assume that, if an individual takes a test and finds out that she has diabetes, she will choose a healthy lifestyle as $u(1,1) > u(1,0)$; if she finds out that she does not have diabetes, she will choose a normal lifestyle given $u(0,0) > u(0,1)$. Hence, the value of taking a screening test ($b = 1$) is:

$$\begin{aligned} V^1(\pi) &= \pi(u(1,1) + M) + (1-\pi)u(0,0) \\ &= 1 - \pi(1-M) \end{aligned} \tag{2}$$

The values of the testing alternatives are depicted in Figure 1.

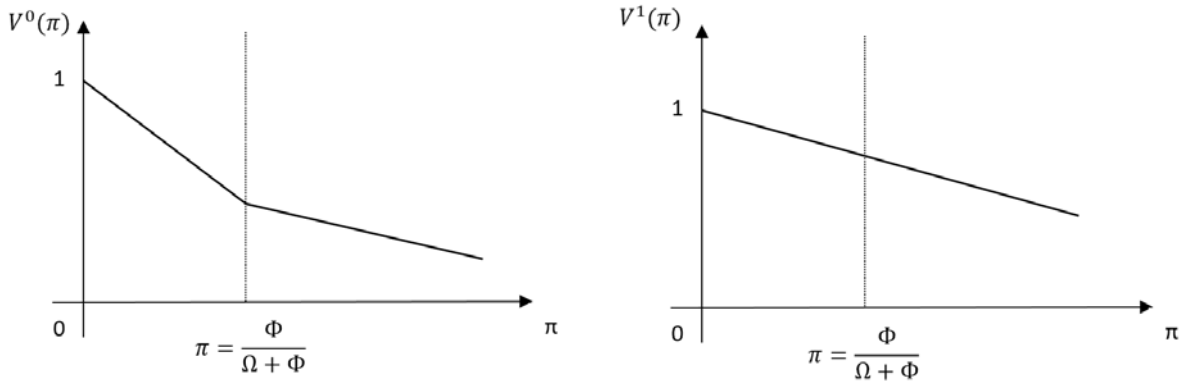


Figure 1: Value of (Not) Taking A Test

Therefore, the marginal benefit from taking a screening test is:

$$\begin{aligned} MB &= V^1(\pi) - V^0(\pi) \\ &= \begin{cases} \pi(M+\Omega) & \text{if } \pi < \frac{\Phi}{\Omega+\Phi} \\ \pi(M-\Phi) + \Phi & \text{if } \pi \geq \frac{\Phi}{\Omega+\Phi} \end{cases} \end{aligned} \tag{3}$$

The marginal cost of taking a screening test is $MC = c$. The individual decides to take a screening test or not according to the marginal benefit and marginal cost as shown in Figure 2.

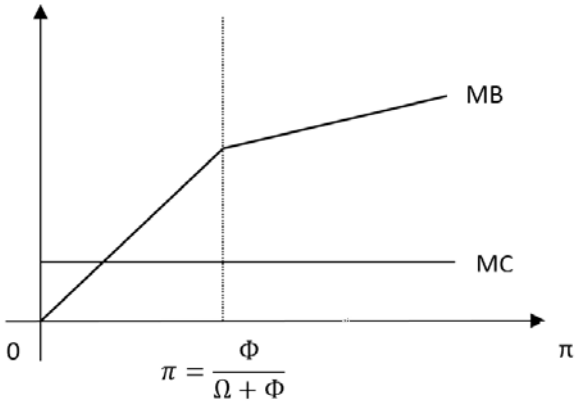


Figure 2: Marginal Benefit and Marginal Cost of Taking A Test

Using this framework and allowing the marginal cost to be random, I simulate testing patterns under different scenarios.

Scenario 1: (baseline scenario) information value only

Let's begin with the baseline scenario, when there is only information value associated with taking a screening test. That is, the individual chooses to take a test only because she can know the state of world and then make the optimal lifestyle decisions. There is no treatment even when the individual is diagnosed with diabetes. For this case, Lemma 1 still holds. The individual chooses to take a test if and only if $MB - MC \geq 0$:

$$\begin{aligned} MB - MC &= V^1(\pi) - V^0(\pi) - MC \\ &= 1 - \pi - V^0(\pi) - c \\ &= \begin{cases} \pi\Omega - c & \text{if } \pi < \frac{\Phi}{\Omega+\Phi} \\ -\pi\Phi + \Phi - c & \text{if } \pi \geq \frac{\Phi}{\Omega+\Phi} \end{cases} \end{aligned} \tag{4}$$

I assume $\Phi = 0.55$ and $\Omega = 0.45$.[4] The value of π is drawn from a normal distribution with mean 0.5 and variance 0.3. Values smaller than 0 or larger than 1 are replaced with the boundary values (i.e., 0 and 1). The cost of taking a test is drawn from a normal

[4]According to the theoretical model and the simulation technique, different values of Φ and Ω will only change the cutoff value of π at which we observe the highest rate of testing.

distribution with mean 0 and variance 0.5.[5] If $MB - MC \geq 0$, the individual takes a screening test, otherwise she does not. The simulated testing pattern for N=1,000,000 individuals is shown in Figure 3. The concave testing pattern indicates that the individuals with beliefs closer to $\pi = \frac{\Phi}{\Omega+\Phi}$ enjoy larger information value. People with π close to 0 and 1 have only a small probability of making a mistake when choosing an optimal lifestyle, thus the information value of a test is small to them.

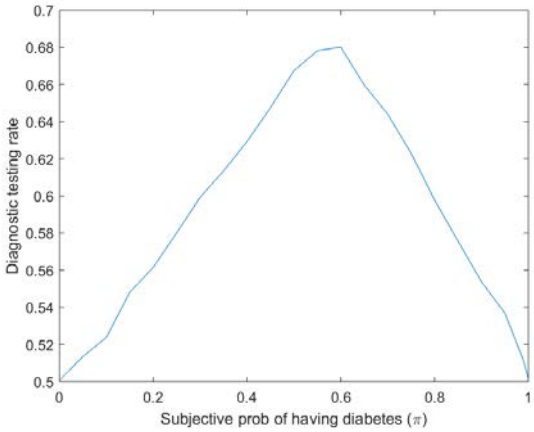


Figure 3: Testing Rate Using Model with Information Value only, $\Phi = 0.55$, $\Omega = 0.45$ and N=1,000,000

3.2 Scenario 2: information and treatment value

Here, I include the treatment value associated with taking a screening test. I assume $M = 0.45$ and re-do the simulation to generate a testing pattern as shown in Figure 4. Different from the baseline scenario, the testing rate of individuals with π larger than the cutoff value remains constant instead of decreasing. This is because, for this group of people, the decreasing information value of testing is compensated by the increasing expected treatment value.

To examine whether my theoretical model captures individuals' behaviors and explains what we observe in the data, I compare the simulated testing behaviors from these two scenarios to the ones we observe in the Health and Retirement Study (HRS) data. Ideally, I want to plot the testing behavior along with the individual's subjective belief of having diabetes. However, I cannot observe this belief information in the data. Therefore, instead, I use an individual's self-reported health status as the measure of subjective belief of having diabetes (π). As we observe in Figure 5, the testing rate increases at

[5] I do not restrict the cost to be positive in the current simulation. That is, an individual may get more value from a test in addition to the information value.

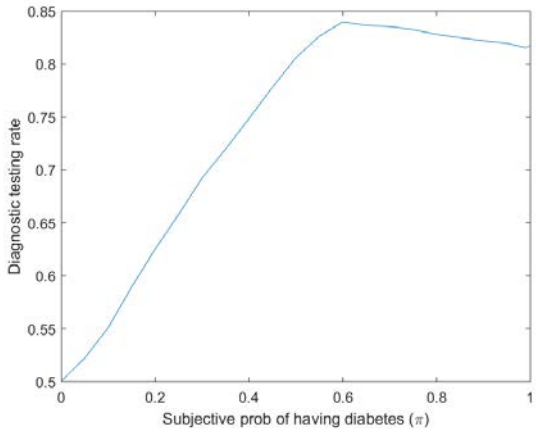


Figure 4: Testing Rate Using Model with Information and Treatment Value, $\Phi = 0.55$, $\Omega = 0.45$, $M = 0.45$ and N=1,000,000

lower values of π and remains constant afterward. This shape is almost identical to the one I simulated for the scenario with both information and treatment value, indicating that the theoretical model with information and treatment value captures individuals' behavior well.

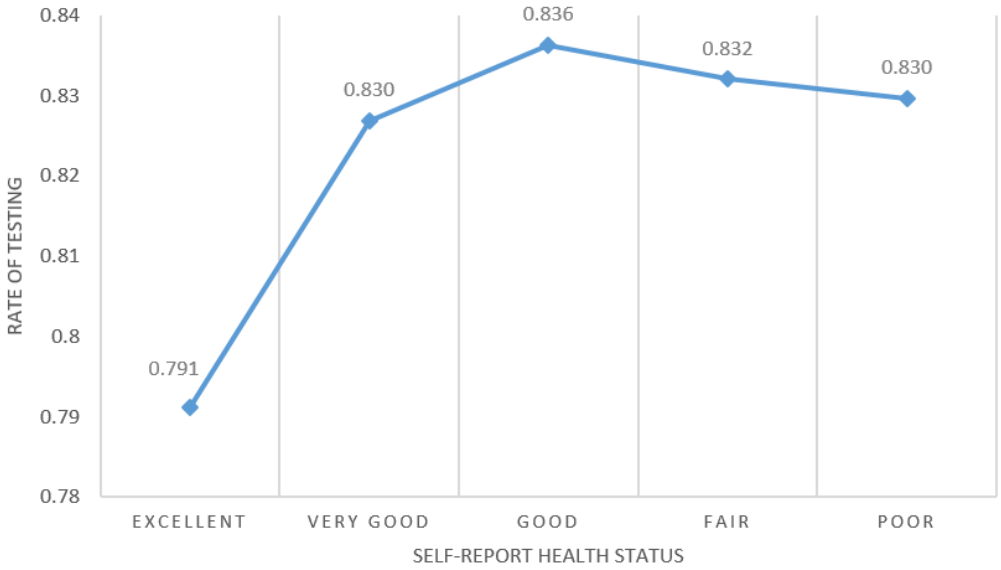


Figure 5: Blood Sugar Test Rate by Self-reported Health Status among Undiagnosed Individuals

But, are the information and treatment values enough to explain the testing behavior? If we divide people in the HRS sample into two groups based on their pessimism levels, we observe that their testing rates are different conditional on self-reported health status

(Figure 6). According to our model, conditional on the subjective probability π, an individual's personality (i.e., pessimism) should not affect the information or treatment value of the test. This testing pattern indicates that there is something missing in our model to explain the different testing behaviors among people with different personalities. According to the theoretical literature, pessimistic individuals, who are more likely to anticipate a bad result, are more likely to suffer from health anxiety. The different testing behavior we observe in the figure by people with different levels of pessimism may be explained after including health anxiety in our model. To keep a parsimonious specification, health anxiety is modeled as an individual-specific characteristic instead of a function of π as in Caplin and Eliaz (2003) or a function of any other variables. The fact that the difference in testing rates between the two groups is fairly constant across the self-reported health status also supports my assumption that health anxiety is not a function of π.

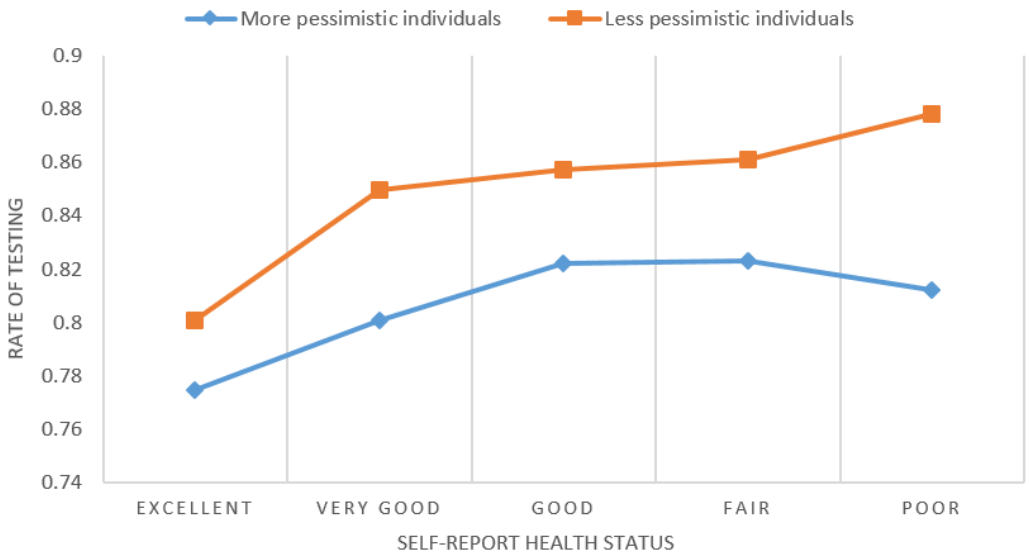


Figure 6: Blood Sugar Test Rate by Self-reported Health Status and Pessimism Level among Undiagnosed Individuals

3.3 Scenario 3: information and treatment value with health anxiety

Finally, I present a model that includes health anxiety as an individual-specific additional cost of taking a test. Alternative theoretical models to explain the behavior of information avoidance are provided in Appendix B. In this model, there are two types of individuals, those who are health anxious and those who are not. Health anxious individuals have an additional cost (A) of taking the screening test due to anticipation of a bad test result:

$MC^A = c+A$. The marginal value of taking a screening test for health anxious individuals is:

$$\begin{aligned} MB - MC^A &= V^1(\pi) - V^0(\pi) - MC^A \\ &= 1 - \pi - V^0(\pi) - c - A \\ &= \begin{cases} \pi(M+\Omega) - c - A & \text{if } \pi < \frac{\Phi}{\Omega+\Phi} \\ \pi(M-\Phi) + \Phi - c - A & \text{if } \pi \geq \frac{\Phi}{\Omega+\Phi} \end{cases} \end{aligned} \tag{5}$$

The marginal value of taking a screening test for non health anxious individuals is the same as that in scenario 2. Assuming that $A = 0.1$, we can simulate the testing pattern as shown in Figure 7.

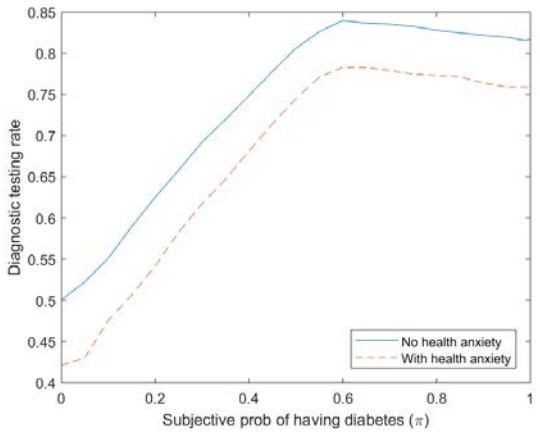


Figure 7: Testing Rate Using Model with Information and Treatment Value and Health Anxiety, $\Phi = 0.55$, $\Omega = 0.45$, $M = 0.45$, $A = 0.1$ and N=1,000,000

4 Data

Although the different testing behavior between people with different pessimism levels is likely to imply the existence of health anxiety, we have not ruled out many other reasons in this simplified setting. People with different personalities could make different life-course decisions such as employment or lifestyle behaviors that lead to different testing behaviors. For example, if less pessimistic individuals are more likely to retire early, then they may have a higher testing rate because they are less constrained by time. Unobservable heterogeneity could be another reason. Furthermore, if we consider dynamics, pessimistic individuals may update their beliefs differently and then have different testing behaviors.

To examine the effect of health anxiety on the demand for diagnostic testing while

accounting for all the dynamic and simultaneous contributors, I jointly estimate a set of approximation equations derived from an individual's optimization problem. In the next section, I introduce the dynamic optimization problem and the empirical estimation method in detail.

In order to measure the empirical contribution of the various contributors to an individual's observed testing behavior, detailed data are required. The primary data from the Health and Retirement Study (HRS) and its linked biomarker data provide the most comprehensive set of variables and appropriate sample size for the empirical investigation. The HRS consists of a longitudinal panel of approximately 28,000 people in the U.S., with biennial observations from 1992 to 2014. The HRS surveys older adults about their physical and mental health, insurance coverage, financial information, family support systems, work status, and retirement planning by in-depth telephone interview.[6] New cohorts of respondents enter the survey every six years.[7] In addition to respondents from eligible birth years, the survey also interviews the spouses of married respondents or the partner of a respondent, regardless of age.

An important data source for my study is the HRS linked biomarker data. In 2006, HRS initiated an Enhanced Face-to-Face Interview (EFTF), which includes a set of physical performance tests, anthropometric measurements, blood and saliva samples, and a self-administered questionnaire on psychosocial topics (the Leave-Behind). The blood and saliva samples are used to evaluate biomarkers in the HRS: saliva is used for DNA extraction and blood is used to measure a range of other biomarkers. A random half of the 2006 sample was selected for the EFTF interview and the other half was selected in 2008. In 2010, the first half was EFTF interviewed again, and in 2012 the second half was interviewed for a second time.[8] This survey method creates a four-year interval between

[6]Health and Retirement Study Website: `http://hrsonline.isr.umich.edu/?_ga=1.174674465.2097313034.1455133775`

[7]The earliest sample cohorts include the "HRS" sample, who were born between 1931 and 1941 (i.e., 51-61 years old at the beginning of the survey) and the "Asset and Health Dynamics among the Oldest Old (AHEAD)" sample, who were born earlier than 1924 (i.e., older than 68 in the first interview). In 1998, the HRS recruited two new sample cohorts: those born between 1924-1930 (CODA, Children of the Depression Era), and those born between 1942-1947 (WB, War Babies). In 2004, a sample born between 1948-1953 (EBB, Early Baby Boomer) was included. In 2010, HRS brought in a new sample cohort born between 1954-1959 (MBB, Middle Baby Boomer). In 2016, HRS started interviewing a sample cohort born between 1960-1965 (LBB, Late Baby Boomer).

[8]Similarly, new sample cohort households in 2010 were randomly assigned into one of these two groups.

the biomarker collection.[9] In the four waves of biomarker sample collection, HRS collected information on five biomarkers: total and HDL cholesterol (indicators of lipid levels), Glycosylated hemoglobin (HbA1c, an indicator of glycemic or glucose control over the past 2-3 months), C-reactive protein (CRP, a general marker of systemic inflammation), and Cystatin C (an indicator of kidney functioning).

4.1 Description of Sample

Constrained by the availability of blood sugar test information, I use data spanning years 2004 to 2012. Of the 28,034 individuals and 98,402 person-wave observations, I exclude observations with missing values for some key variables (10.1 percent). To estimate the dynamic model, I retain respondents who have at least two waves of survey information, reducing the estimation sample to 21,541 respondents with 77,881 person-wave observations. The distribution of the number of observed waves is detailed in Table 1.

Table 1: Distribution of research sample by year and waves

	# Observations	# Respondents	# Death	# Attrition
# Respondents in 2004	14,586	14,586	0	0
# Respondents in 2006	15,484	15,484	823	1,060
# Respondents in 2008	14,522	14,522	986	1,175
# Respondents in 2010	17,497	17,497	688	1,017
# Respondents in 2012	15,792	15,792	0	0
Sample with 5 waves	46,805	9,361	0	0
Sample with 4 waves	7,808	1,952	576	807
Sample with 3 waves	8,436	2,812	960	1,126
Sample with 2 waves	14,832	7,416	961	1,319
Estimation Sample	77,881	21,541	2,497	3,252

Key information

My empirical investigation of the contributors to preventive testing behavior is applied to blood sugar screening and diabetes risks. The HRS provides important information

[9] In 2006, the blood sample consent rate was 83%, the completion rate, conditional on consent, was 97%, and the overall completion rate was 81%. In 2008, the blood sample consent rate was 87%, the completion rate, conditional on consent, was 100%, and the overall completion rate of 87%. In 2010, the blood sample consent rate was 85%, the completion rate, conditional on consent, was 99%, and the overall completion rate was 84%. In 2012, the blood sample consent rate was 87%, the completion rate, conditional on consent, was 99%, and the overall completion rate of 86%.

necessary for assessing an individual's probability of having a blood sugar test, including the number of doctor visits and nights of hospitalization, blood sugar testing and test results. The summary statistics for the key variables are in Table 2.

First, I use the blood sugar test information from the HRS survey. In the 2004-2012 surveys, the individuals who are not diagnosed with diabetes are asked the question "Since the previous interview, have you had a blood test for your blood sugar?" For respondents with diabetes, this question is skipped in the survey as individuals with diabetes are instructed to regularly monitor their blood sugar levels. Among the undiagnosed person-wave observations, the average blood sugar test rate in a two-year period is 0.827. I also observe the self-reported diagnosis outcome if the individual is diagnosed with diabetes from the diabetes stage questions in HRS: "Has a doctor ever told you that you have diabetes or high blood sugar?", "In order to treat or control your diabetes, are you now taking medication that you swallow?" and "Are you now using insulin shots or a pump?". The diabetes stages show that 79 percent of person-wave observations are not diagnosed with diabetes, 3.2 percent are diagnosed with diabetes but do not have any medical treatment, 12.9 percent are diagnosed with diabetes and take some oral medications, and 5 percent are diagnosed with diabetes and treated with insulin shots.

I observe an individual's true A1c value from the HRS linked bio-marker data set every four years. Among the observed values, the average A1c is 5.884. Based on medical guidelines, I define those with A1c values lower than 5.7 to have normal levels, those with A1c values between 5.7 and 6.4 to be pre-diabetic, and those with A1c values higher than 6.4 to be diabetic. Accordingly, 55.4 percent of the non-missing estimation sample have A1c readings in the normal range, 27.9 percent have A1c readings in the pre-diabetic range, and 16.7 percent have A1c readings in the diabetic range.

The average number of doctor visits (over a two-year period) is 10.723 with 7.2 percent of observations having no doctor visits. Regarding nights in hospitals, 74.4 percent of person-wave observations have no hospital nights (over a two-year period). Among those who have any hospital nights, the average number of hospital nights is 8.341.

Lifestyle behaviors

Because diabetes prevention includes lifestyle behaviors, I also desire information on body mass and nutrition, exercise, smoking, and drinking behaviors (Table 2).

It is widely acknowledged that body mass (or body mass index, BMI) is an important predictor of diabetes risk (Narayan et al., 2007). In the estimation sample, the average body mass index value is 28.33, with 29.1 percent of observations having normal BMI, 1.5 percent being underweight, 36.8 percent being overweight, and 32.7 percent being obese.

Unfortunately, I do not observe nutrition (or diet) behavior in the HRS. However, the diet and nutrition information could potentially be reflected by the BMI evolution after conditioning on the level of exercise.

In the HRS, exercise information is collected using three questions about the frequencies of vigorous, moderate and mild exercise. The responses include 5 categories: (1) everyday, (2) more than once a week, (3) once a week, (4) one to three times a month, and (5) hardly ever or never. I group (1) and (2) as high level, (3) and (4) as low level, and (5) as never, for each type of exercise. To simplify the exercise level measures, I construct an aggregate exercise variable based on frequencies of each type of exercise.[10] In the sample, 22.9 percent of observations have no exercise, 21.5 percent have mild level of exercise, 31.5 percent have moderate exercise and 24.2 percent have vigorous exercise. I also observe smoking and drinking behaviors: 14.1 percent of person-wave observations are observed to smoke and 11.4 percent are observed to binge drink, which is defined as having 4 or more drinks in at least one day in the past three months.

Perception of health

Since individuals may make decisions using imperfect information about own health, some information about the individual's perception about health is required. I observe the individual's self-reported health status and subjective survival probability in the HRS (Table 2).

The self-reported health status contains five categories: excellent, very good, good, fair, and poor. Almost a third of observations report good health status, 10.7 percent report excellent, 30.0 percent report very good, 19.9 percent report fair, and only 7.8 percent report poor. Based on the longevity expectation questions collected by HRS, a subjective two-year survival probability is calculated for each person-wave observation using the method in Wang (2014) and Perozek (2008). More details about the method can be found in Appendix C. The two longevity expectation questions in the HRS are: (1) "What is the percent chance that you will live to be 75 or more?"; (2) "What is the percent chance that you will live 10 more years (to be age [85/80/90/95/100] or more)?"

[10]Specifically, different alternatives are modeled as: *no exercise* includes low/never mild exercise, never/low moderate, and never vigorous; *mild exercise* includes high mild, low/never moderate, low/never vigorous, and low/never mild, low/never moderate, and low vigorous; *moderate exercise* includes high-/low/never mild, high moderate, low/never vigorous; and *vigorous exercise* includes high/low/never mild, high/low/never moderate, and high vigorous.

Employment

Employment behavior also determines income and available time for preventive care. I observe different employment statuses in the HRS (Table 2). In the estimation sample, 68.6 percent of individual-wave observations are not working, including those who are retired and those who are unemployed. This high rate of non-employment reflects that a majority of the individuals in the estimation sample are approaching or past retirement age. There are 5.6 percent of observations working part-time and 25.7 percent working full-time.

Table 2: Summary statistics for endogenous variables

Variable	Mean	S.D.	Min	Max
Number of doctor visits (over two years	10.723	19.933	0.000	900.000
Doctor visits: none	0.072	0.258	0.000	1.000
Doctor visit: low (≤ 10)	0.652	0.476	0.000	1.000
Doctor visit: high (> 10)	0.276	0.447	0.000	1.000
Employment: none	0.686	0.464	0.000	1.000
Employment: part-time	0.056	0.230	0.000	1.000
Employment: full-time	0.257	0.437	0.000	1.000
Exercise: none	0.229	0.42	0.000	1.000
Exercise: mild	0.215	0.411	0.000	1.000
Exercise: moderate	0.315	0.465	0.000	1.000
Exercise: vigorous	0.242	0.428	0.000	1.000
Smoking	0.141	0.348	0.000	1.000
Binge Drinking	0.114	0.317	0.000	1.000
Blood sugar test (if undiagnosed)	0.827	0.379	0.000	1.000
Diabetes: no diagnosis	0.790	0.408	0.000	1.000
Diabetes: diagnosed without medical treatment	0.032	0.175	0.000	1.000
Diabetes: diagnosed with oral medication	0.129	0.335	0.000	1.000
Diabetes: diagnosed with insulin shot	0.050	0.218	0.000	1.000
Any hospitalization night (over two years)	0.256	0.436	0.000	1.000
Number of hospitalization nights (if any)	8.341	16.475	1.000	609.000
True A1c value (if not missing)	5.884	1.025	3.010	17.170
True A1c: normal (if not missing)	0.554	0.497	0.000	1.000
True A1c: pre-diabetic (if not missing)	0.279	0.448	0.000	1.000
True A1c: diabetic (if not missing)	0.167	0.373	0.000	1.000
True A1c: missing	0.703	0.457	0.000	1.000
BMI value	28.338	6.025	9.765	75.801
BMI: normal	0.291	0.454	0.000	1.000
BMI: underweight	0.015	0.123	0.000	1.000
BMI: overweight	0.368	0.482	0.000	1.000
BMI: obese	0.327	0.469	0.000	1.000
Self-report health: excellent	0.107	0.309	0.000	1.000
Self-report health: very good	0.300	0.458	0.000	1.000
Self-report health: good	0.316	0.465	0.000	1.000
Self-report health: fair	0.199	0.399	0.000	1.000
Self-report health: poor	0.078	0.269	0.000	1.000
Two-year survival probability	0.854	0.222	0.083	1.000
Death	0.032	0.176	0.000	1.000

Personality measures and exogenous characteristics

Lastly, I observe pessimism in the HRS, which is used to approximate health anxiety. Since the pilot survey in 2004, the HRS has included a psychosocial and lifestyle questionnaire

in each biennial wave for a rotating random 50 percent of the core panel participants who complete the EFTF interview. That is, the longitudinal data for personality measures are available at four-year intervals. To solve this problem, I use the average value of an individual's observed personality measures over time to fill in values in all waves. By doing this, personality measures are treated as time-invariant individual characteristics. Besides pessimism (6 items, score ranging from 1-6), I also observe some other personality measures: anxiety (5 items, score ranging from 1-4), and the "Big 5" personality traits (31 items) that include neuroticism, extroversion, openness, agreeableness, and conscientiousness (all scores ranging from 0-4). More detailed information about the survey items for each personality measure are in Appendix D. Table 3 depicts the summary statistics of the personality measures. At the individual level, the average pessimism score is 2.537. A missing indicator is also created if an individual has a missing value for all personality measures.

Additionally, I also observe a rich set of the individual's exogenous characteristics in HRS (Table 3). In the estimation sample, the average age is 66.806 and about 60 percent are women. Three quarters are white, 18 percent are African American, and 7 percent are another race. Regarding education, about 50 percent of individuals have a high-school degree, 20 percent have no degree and 28 percent have a college or higher degree.

Table 3: Summary statistics for personality and exogenous variables

Variable	Mean	S.D.	Min	Max
Personality variables				
Pessimism	2.537	0.922	1.000	6.000
Anxiety	1.587	0.576	1.000	4.000
Neuroticism	2.047	0.592	1.000	4.000
Extroversion	3.184	0.542	1.000	4.000
Openness	2.932	0.542	1.000	4.000
Agreeableness	3.518	0.465	1.000	4.000
Conscientiousness	3.298	0.428	1.000	4.000
Missing personality measures	0.191	0.392	0.000	1.000
Exogenous individual characteristics				
Age	66.806	11.153	18.000	109.000
Female	0.587	0.492	0.000	1.000
Race				
White	0.751	0.433	0.000	1.000
Black	0.176	0.381	0.000	1.000
Other	0.072	0.260	0.000	1.000
Education				
No degree	0.199	0.399	0.000	1.000
High school	0.526	0.499	0.000	1.000
College	0.191	0.393	0.000	1.000
Higher than college	0.084	0.277	0.000	1.000
Marital status				
Married	0.619	0.486	0.000	1.000
Partnered	0.040	0.197	0.000	1.000
Separated	0.017	0.13	0.000	1.000
Divorced	0.105	0.306	0.000	1.000
Widowed	0.181	0.385	0.000	1.000
Never married	0.038	0.19	0.000	1.000
Log(household income)	10.460	1.459	0.000	17.910
Census region				
Northeast	0.153	0.360	0.000	1.000
Midwest	0.244	0.429	0.000	1.000
Western	0.405	0.491	0.000	1.000
Southern	0.198	0.398	0.000	1.000

Note: Summary statistics for time-invariant variables (i.e., the personality variables, gender, race, and education) are at the individual level.

5 Empirical Framework

In this section, I describe the empirical framework I use to examine the effects of many contributors, including health anxiety, on an individual's demand for diabetes screening. Initially, I introduce the timing and notation of an individual's dynamic decisionmaking process where, given updated information each period, she evaluates alternative health-related behaviors and optimally chooses given uncertain health evolution in the future. The theory provides a framework for deriving optimal demand equations and health production functions that form a set of dynamic correlated equations that can be jointly estimated. Having specified the theoretically-motivated arguments of these equations, I then discuss the estimation strategy and identification in detail.

5.1 Individual decision-making process

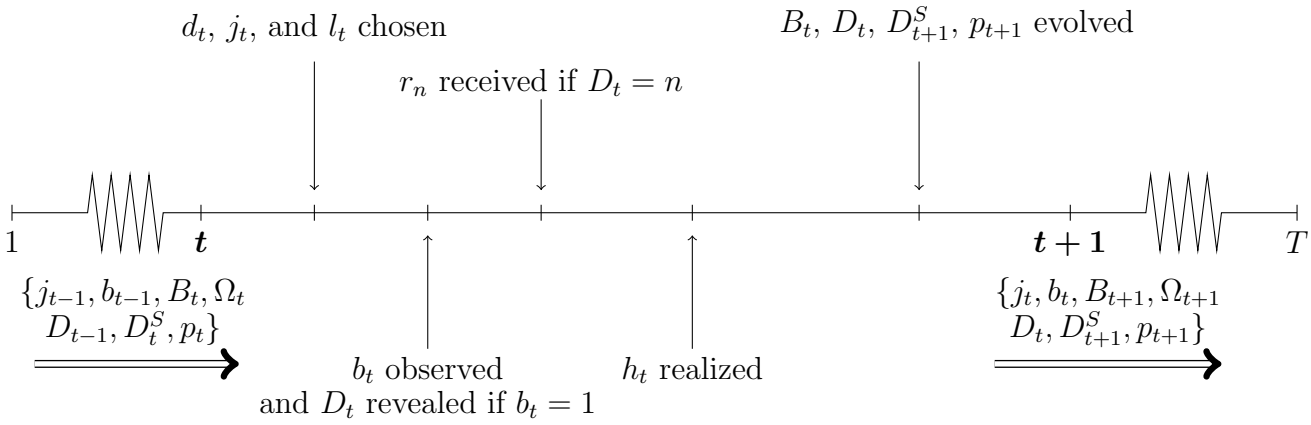
The timing of decisionmaking within a period is depicted in Figure 8. Knowing past employment and screening behaviors (j_{t-1} and b_{t-1}), body mass (B_t), and relevant exogenous information (denoted by the vector Ω_t and explained in more detail in section 5.2), an individual enters each period with a revealed true disease status D_{t-1} (conditional on previous testing behaviors), a subjective disease status D_t^S, and a subjective two-year survival probability p_t. The underlying disease state is not known by the individual if not tested. While individuals are unlikely to initiate a diabetes screening test directly (i.e., without a doctor visit), a visit to a doctor may result in a recommendation for screening, which the patient may or may not accept. Because such tests may require a follow up visit or a blood draw in a different location, a patient may or may not comply with the recommendation. I allow for the role of physician agency in the individual's optimization problem in the following way. Individuals choose the number of doctor visits per period, d_t. If an undiagnosed individual has any doctor visits in this period, she faces a probability of getting a blood sugar test, b_t, or a diabetes screening. The individual's true disease state is revealed if she gets the blood sugar test. That is, the individual's true disease becomes her known disease state. If the individual is diagnosed with diabetes stage n $[(D_t = n|b_t = 1)$ and $n > 0]$, she is assumed to receive a stage-specific treatment r_n and to have blood sugar tests in every subsequent period regardless of doctor visits.[11] The individual also faces a probability of hospitalization, h_t, in each period.

In addition to choosing the number of doctor visits, an individual also chooses em-

[11]The assumption of a blood sugar test each period after diagnosis is supported by data. Individuals diagnosed with diabetes must monitor their blood sugar regularly. Additionally, respondents in the HRS who have been diagnosed with diabetes are not asked about their blood sugar testing behavior.

ployment, and other health-related lifestyle behaviors. Employment is modeled because it impacts the time available for health-producing activities as well as resources for consumption. The employment alternatives are non-employment, part-time employment, and full-time employment.[12] The lifestyle behaviors capture non-medical care inputs that impact health. I model exercise, smoking, and binge drinking behavior, denoted by $l_t = [l_t^1, l_t^2, l_t^3]$. Nutrition is an important input, but this information is not available in the HRS data. Nutrition behavior may be reflected by body mass changes conditional on the level of exercise.

Figure 8: Timing



In the model, an undiagnosed individual may not receive a blood sugar test for two reasons: she has a low level of doctor visits and/or she has a low probability of getting a test conditional on the level of doctor visits. Several aspects of the individual's optimization problem influence her optimal number of doctor visits each period. These contributors (and their location in the optimization problem) are: (1) monetary cost of doctor visits (budget constraint); (2) time cost of doctor visits (time constraint); (3) incorrect expectations of the productivities of medical care and non-medical care inputs in disease evolution (health production functions); (4) life expectancy (survival probability and value function); (5) health anxiety of getting the test (a potential utility cost distinct from the disutility of illness). Similarly, factors that influence the probability of a blood sugar test conditional on the number of doctor visits are: (1) monetary cost of tests (budget constraint); (2) time cost of tests (time constraint); (3) observable individual characteristics associated with diabetes risk (i.e., body mass and family health)(screening recommendation/offer); and (4) the individual's tendency to avoid or refuse a test during doctor visits (i.e., health anxiety and short life expectancy)(utility and value function).

[12] An individual choosing not to work may be retired, unemployed, disabled or out of the labor force.

5.2 Estimable equations

Using the theoretical framework that defines an individual's optimization problem with regard to blood sugar testing, I form a set of approximation equations to the discrete choice behaviors derived from solution to the individual's optimization problem.[13] I jointly estimate the derived demand equations, the stochastic outcomes, and the production functions that make up each individual's per-period contribution to a likelihood function. The demand equations are functions of the endogenous and exogenous variables known to the individual at the beginning of each period.[14] The health production equations are functions of the medical and non-medical care behaviors observed during the period. All equations are allowed to be correlated contemporaneously (i.e., within a period) and across time through permanent and time-varying unobserved heterogeneity. For each equation k, the error term is decomposed into three parts: a permanent unobserved heterogeneity component (μ^k), a time-varying unobserved heterogeneity component (ν_t^k) and an idiosyncratic error term (ϵ_t^k) where:

$$e_t^k \;=\; \mu^k + \nu_t^k + \epsilon_t^k$$

The idiosyncratic error terms (ϵ_t^k) are assumed to be i.i.d Type-1 Extreme value distributed for discrete outcome equations and i.i.d normally distributed for continuous outcome equations. I discuss estimation of the distribution of the first two components in section 5.3. The specification of each equation is summarized in Table A of Appendix E.

5.2.1 Demand Equations

The five demand equations that approximate the five discrete choice behaviors include the number of doctor visits, employment, and the levels of exercise, smoking, and binge drinking. To reflect that the individual makes those decisions simultaneously, the demand equations share the same set of determinants. Specifically, each demand equation is a function of the individual's past employment behavior (j_{t-1}), body mass (B_t), exogenous information (Ω_t), the revealed true disease state (D_{t-1}) entering period t interacted with the past screening behavior (b_{t-1}), and the subjective disease state (D_t^S) and survival probability (p_t).

The vector of exogenous information ($\Omega_t = \{X_t, W_t, Z_t, P_t\}$) includes a vector of in-

[13] A detailed theoretical model is available from the author but is not specified here because it is not formally estimated.

[14] The estimated parameters in the demand equations represent the marginal effects of variables on the observed discrete choice, and are functions of the underlying primitive parameters in an individual's utility, constraints, and expectations that form the decisionmaking problem.

dividual characteristics (X_t: age, gender, race, education, marital status, log household income, and residence census region); a vector of personality measures (W_t: pessimism, anxiety, and the "big 5" personality traits that include neuroticism, extroversion, openness, agreeableness, conscientiousness); indicators of health insurance (Z_t^H) and a vector of parental mortality variables (Z_t^P: indicator of death of the same gender parent, age of alive same gender parent, age of death of same gender parent); and a vector of regional characteristics to capture supply side medical care conditions, demand side employment conditions, and exogenous health determinants (P_t). I detail the variables in the vector P_t in the identification section.

Level of doctor visits

Individuals choose the number of doctor visits each period. The number of doctor visits is discretized to reduce the number of alternatives. This discretization also reduces some measurement error in the data. The cutoff points of the discretization are based on the mean in the sample: those who have 10 or fewer doctor visits are defined to have a low level of visits and those who have more than 10 doctor visits are defined to have a high level of visits. In the sample, 65.2 percent of person-wave observations have a low level of doctor visits, 27.6 percent have a high level of doctor visits, and 7.2 percent have no doctor visits over the period of two years (Table 2). To account for the possibility of observing an undiagnosed individual who has no doctor visits but reports having a blood sugar test, the alternative of "no doctor visit" is further discretized to "no doctor visit but test" and "no doctor visit and no test".[15] Because the alternative "no doctor visit and no test" is not available for individuals who have already been diagnosed with diabetes, I estimate the doctor visit equation among individuals with diagnosed diabetes separately. The determinants of the two equations are the same.

For an individual who is not previously diagnosed with diabetes, the probabilities of choosing no doctor visit and no test ($d_t = 0|D_{t-1} = 0$), or no doctor visit but test ($d_t = 1|D_{t-1} = 0$), or a high level of doctor visits ($d_t = 3|D_{t-1} = 0$) relative to choosing a low level of doctor visits ($d_t = 2|D_{t-1} = 0$) are:

$$ln[\frac{p(d_t = d|D_{t-1} = 0)}{p(d_t = 2|D_{t-1} = 0)}] = f_d^{DU}(j_{t-1}, D_{t-1} * b_{t-1}, D_t^S, B_t, p_t, X_t, W_t, Z_t, P_t, \mu^{D^U}, \nu_t^{D^U}), \quad d = 0, 1, 3 \tag{6}$$

[15] These tests might be performed at pharmacies, during hospital stays, and in labs without a doctor visit.

For an individual who has been diagnosed with diabetes, the probabilities of choosing no doctor visit ($d_t = 1|D_{t-1} > 0$) or a high level of doctor visits ($d_t = 3|D_{t-1} > 0$) relative to choosing a low level of doctor visits ($d_t = 2|D_{t-1} > 0$) are:

$$ln[\frac{p(d_t = d|D_{t-1} > 0)}{p(d_t = 2|D_{t-1} > 0)}] \;=\; f_d^{DD}(j_{t-1}, D_{t-1} * b_{t-1}, D_t^S, B_t, p_t, X_t, W_t, Z_t, P_t, \mu^{D^D}, \nu_t^{D^D}), \quad d = 1, 3 \tag{7}$$

Employment

The probabilities of being employed part-time ($j_t = 1$) or full-time ($j_t = 2$) relative to being non-employed (i.e., either retired or unemployed) are:

$$ln[\frac{p(j_t = j)}{p(j_t = 0)}] \;=\; f_j^J(j_{t-1}, D_{t-1} * b_{t-1}, D_t^S, B_t, p_t, X_t, W_t, Z_t, P_t, \mu^J, \nu_t^J) \;,\; j = 1, 2 \tag{8}$$

Lifestyle behaviors

Relative to the probability of choosing moderate amount of exercise ($\ell_t^1 = 2$), the probability of choosing no exercise ($\ell_t^1 = 0$), mild exercise ($l_t^1 = 1$), or vigorous exercise ($\ell_t^1 = 3$) are:

$$ln[\frac{p(\ell_t^1 = \ell)}{p(\ell_t^1 = 2)}] \;=\; f^{L1}(j_{t-1}, D_{t-1} * b_{t-1}, D_t^S, B_t, p_t, X_t, W_t, Z_t, P_t, \mu^{L^1}, \nu_t^{L^1}) \;,\; \ell = 0, 1, 3 \tag{9}$$

The probability of choosing to smoke ($\ell_t^2 = 1$) relative to non-smoking ($\ell^2 = 0$) is:

$$ln[\frac{p(\ell_t^2 = 1)}{p(\ell_t^2 = 0)}] \;=\; f^{L2}(j_{t-1}, D_{t-1} * b_{t-1}, D_t^S, B_t, p_t, X_t, W_t, Z_t, P_t, \mu^{L^2}, \nu_t^{L^2}) \tag{10}$$

The probability of binge drinking ($\ell_t^3 = 1$) relative to not binge drinking ($\ell_t^3 = 0$) is:

$$ln[\frac{p(\ell_t^3 = 1)}{p(\ell_t^3 = 0)}] \;=\; f^{L3}(j_{t-1}, D_{t-1} * b_{t-1}, D_t^S, B_t, p_t, X_t, W_t, Z_t, P_t, \mu^{L^3}, \nu_t^{L^3}) \tag{11}$$

5.2.2 Stochastic outcomes

Following the timing of the individual's decisionmaking process, whether or not the individual had a blood sugar test and nights in the hospital are realized sequentially after the individual has chosen doctor visits, employment, and lifestyle behaviors. Hence, current

period behaviors may influence these stochastic realizations. Specifically, the levels of doctor visits and health-related behaviors in the current period affect both the probability of having a blood sugar test (among undiagnosed individuals with at least one doctor visit) and the number of hospital nights.

Blood sugar test

If the individual has not been diagnosed with diabetes and has at least one doctor visit, her probability of ***not*** having a blood sugar test ($b_t = 0$) relative to the probability of having a blood sugar test ($b_t = 1$) is:

$$ln[\frac{p(b_t = 0|D_{t-1} = 0,\ d_t > 1)}{p(b_t = 1|D_{t-1} = 0,\ d_t > 1)}] \ = \ f^{PB}(d_t, j_t, \ell_t, D_t^S, B_t, p_t, X_t, W_t, Z_t, P_t^M \mu^{PB}, \nu_t^{PB}) \tag{12}$$

where d_t, j_t, and ℓ_t are the levels of doctor visits, employment, and health-related lifestyle behaviors (i.e., exercise, smoking, and binge drinking), respectively. In addition to own subjective disease state (D_t^S) and body mass (B_t), the same gender parent's mortality measures (Z_t^P) are included to approximate family health history, which is an important guideline for physician's initial suggestion/prescription of blood sugar tests. Health insurance (Z_t^H) captures the price of having a diabetes screening for the individual. Regional medical supply factors (P_t^M) are also included to capture the physician's role in affecting an individual's blood sugar testing behavior. Conditional on the endogenous behaviors, health states, and other personality measures, the marginal effect of pessimism evaluates whether pessimistic individuals are more likely to avoid a test due to health anxiety (i.e., the additional psychological cost of anticipating a bad result).

If an undiagnosed individual has no doctor visits this period, the probability of blood sugar testing is $p(b_t = 1|D_t = 0,\ d_t \leq 1) = d_t$, where $d_t = 0$ or 1 captured by equation 6.

If the individual has been diagnosed with diabetes when entering this period (i.e., $D_t > 0$), the probability of a blood sugar test is one. $p(b_t = 1|D_t > 0) \ = \ 1$.

Nights in hospital

Given that three-fourths of the observations in the sample are not hospitalized within a 2-year period (Table 2), I model the number of hospital nights in two parts. A logit model is used to estimate the probability of having any hospitalization. The probability

of having any hospital nights ($h_t > 0$) relative to having no hospital nights ($h_t = 0$) is:

$$ln[\frac{p(h_t > 0)}{p(h_t = 0)}] \;=\; f^H(d_t, j_t, \ell_t, D_t * b_t, D_t^S, B_t, X_t, Z_t^H, P_t^M, \mu^H, \nu_t^H) \tag{13}$$

For those who have non-zero hospital nights, an equation for the number of hospital nights is specified as

$$h_t | h_t > 0 \;=\; f^H(d_t, j_t, \ell_t, D_t * b_t, D_t^S, B_t, X_t, Z_t^H, P_t^M, \mu^H, \nu_t^H) \tag{14}$$

Both equations are functions of current period behaviors, the interaction between a blood sugar test and revealed true stage of diabetes ($D_t * b_t$), the self-perception of health (D_t^S), and body mass (B_t) entering the period. The specification includes Z_t^H and P_t^M to capture the impacts of price and regional medical care supply factors that may influence the observed number of nights. An interaction term between the level of doctor visits and diabetes diagnosis may capture the potential protection effect of doctor visits (i.e., catch illness early) or signal health declines not captured by disease state, body mass, and longevity expectations.

5.2.3 Health production functions

Health evolves from one period to the next. The dynamic health outcomes include blood sugar levels, body mass evolution, and death.

Blood sugar level

The blood sugar level is measured by readings from an A1c test, also called the hemoglobin A1c, HbA1c, or glycohemoglobin test in the HRS biomarker data (Table 2). A higher reading represents a higher blood sugar level (i.e., less healthy). Regardless of whether an individual learns her true disease state (by taking a blood sugar test), her blood sugar level is evolving. The HRS data provide the A1c values of individuals for whom a blood sample is collected, independent of doctor visits and observed diabetes screening behaviors. That is, the entire randomly-selected sample receives a test at some point. With these data, I can explain A1c value transitions as individuals age, which is unobservable to the individuals but governs their true disease transitions. In other words, this process does not enter an individual's optimization problem directly, but it allows me, as the econometrician, to capture the underlying health production and therefore explain observed health outcomes better.

I allow blood sugar levels (A_{t+1}) to depend on an individual's period t behaviors and

hospitalization to capture medical and non-medical inputs, and the previously known diabetes state ($D_t * b_t$) to capture persistence as well the medical treatment an individual receives if she is diagnosed with diabetes. It also depends on the self-reported health status (D_t^S) since this measure has been shown to correlate well with the true disease state, which is unknown if undiagnosed. Blood sugar level also depends on body mass, which is a good predictor of diabetes, and the same gender parent's mortality measures (Z_t^P) to approximate the genetic inheritance from the parent that predict diabetes. I estimate the blood sugar production equations using observations from the research sample for which it is observed and I am able to use this estimated process to simulate A1c values for all observations when evaluating marginal effects of interest in the dynamic simulations. Specifically, determinants of A1c are

$$A_{t+1} = f^A(d_t, j_t, \ell_t, h_t, D_t * b_t, D_t^S, B_t, X_t, Z_t^P, \mu^A, \nu_t^A) \tag{15}$$

Body mass

Body mass is measured using a body mass index (BMI) that depends on weight and height.[16] The evolution of BMI depends on medical care inputs (d_t and h_t) as well as non-medical care health behaviors (ℓ_t). The lagged BMI value is included to capture the persistence of body mass evolution. In the empirical specification, I include interaction terms between the lagged BMI category (i.e., underweight, normal, overweight and obese) and the continuous value of lagged BMI to allow for persistence in a non-linear way.[17] The revealed true disease state interacted with diabetes screening behavior is included for two reasons. First, it aims to examine whether individuals respond to the health information gained from taking a test. That is, the interaction term evaluates whether the individual who takes a test responds to the information and produces BMI differently through the unobserved nutrition/diet behavior. Second, since some reports show that weight is sensitive to insulin level in blood and weight gain is not an uncommon phenomenon among people using insulin as a treatment, the revealed true disease state, which defines the type of treatments the individual receives (if diagnosed with diabetes), captures this effect. Another interaction term between screening behavior and lagged BMI is included to capture the heterogeneous effects of no test on BMI evolution. I also include employment behavior (j_t) and subjective 2-year survival probability (p_t) that are likely to influence the unobserved dieting behavior and thus the BMI evolution. Finally, the production of

[16]The BMI is defined as the weight (kg) divided by the square of height (m^2).

[17]The BMI categories are defined as: those with BMI values lower than 18.5 are underweight; those with BMI values between 18.5 and 25 are normal; those with BMI values between 25 and 30 are overweight, and those with BMI values larger than 30 are obese.

BMI also depends on regional health-related price and supply side variables (explained in more details in section 5.3) and unobserved heterogeneity. That is,

$$B_{t+1} \;=\; f^B(d_t, j_t, \ell_t, h_t, D_t * b_t, D_t^S, B_t, p_t, X_t, P_t^H, \mu^B, \nu_t^B) \tag{16}$$

Death

I model death as another endogenous health outcome which may result after a decline in health or as a health shock. Consequently, it depends on the individual's histories of past health events and outcomes. The outcome of death is observed at the end of the period, after the updating or realization of all other health outcomes. As a result, the probability of death is a function of an individual's updated revealed true disease state, subjective health status and survival probability, hospital nights, body mass, parental mortality measures (to capture the inherited genetics about life longevity from the same gender parent), regional medical care-related price and supply side factors, an individual's exogenous characteristics, and unobserved heterogeneity. The probability of death, $E_{t+1}^D = 1$, conditional on being alive this period, $E_t^D = 0$, relative to survival ($E_{t+1}^D = 0$), is

$$ln[\frac{P(E_{t+1}^D = 1|E_t^D = 0)}{P(E_{t+1}^D = 0|E_t^D = 0)}] \;=\; f^{ED}(h_t, D_t{*}b_t, D_{t+1}^S, B_{t+1}, p_{t+1}, X_t, Z_t^P, P_t^M, \mu^{ED}, \nu_t^{ED}) \tag{17}$$

5.2.4 Health expectation processes

Subjective disease state

The subjective disease state is measured by self-reported health status from the HRS data set. This categorical variable has five response categories (denoted by s): "Excellent", "Very Good", "Good", "Fair" and "Poor" (Table 2). According to theory, an individual solves the optimization problem based on her subjective disease state (regardless of the testing behavior), which might over-estimate or under-estimate the true disease state. But, once the individual takes a test, her beliefs become "better" or closer to the truth. Therefore, the evolution of an individual's self-reported health status should reflect that the individual incorporates the new information regarding her true disease state once tested. In the estimated production function, this idea is embodied by the inclusion of interaction terms between the revealed true disease state, lagged BMI and the blood sugar test behavior ($D_t * b_t$ and $B_t * b_t$). In other words, the interaction terms allow the individual to update the self-reported health status differently depending on whether or not she takes a test and the diagnosed stage of diabetes if tested.

The production of this subjective disease state is a function of behaviors in the current period, lagged subjective disease state (to capture persistence), BMI, revealed true disease state, and the subjective survival probability entering in this period. It also depends on the personality measures, since one's own self-perception of health is shown to be highly correlated with own personality traits (Goodwin and Engstrom, 2002). The probabilities of reporting "excellent" ($s_{t+1} = 0$), "very good" ($s_{t+1} = 1$), "fair" ($s_{t+1} = 3$), or "poor" ($s_{t+1} = 4$) health relative to the probability of reporting "good" health ($s_{t+1} = 2$) are:

$$ln[\frac{p(D^S_{t+1} = s)}{p(D^S_{t+1} = 2)}]] \;=\; f^S(d_t, j_t, \ell_t, h_t, D_t * b_t, D^S_t, B_t, B_t * b_t, p_t, X_t, W_t, \mu^S, \nu^S_t), \quad s = 0, 1, 3, 4 \tag{18}$$

Subjective survival probability

In addition to the subjective disease state, an individual also reports a subjective two-year survival probability entering each period. This probability is used to capture an important contributor to why an individual may not take a blood sugar test: it has a low future payoff due to a short life expectancy. An individual's subjective two-year survival probability depends on her chosen health inputs, and her observed or subjective disease state and body mass in the current period. To reflect the information value of taking a test on forming the subjective survival probability, an interaction term between revealed true disease state and the blood sugar testing behavior is included. Furthermore, interaction terms between the screening test behavior and self-reported health status and BMI are included in order to allow for heterogeneous effects of information. The individual's personality measures, same gender parent's mortality measures, exogenous characteristics, and unobserved heterogeneity also influence her formation of subjective survival probability. The continuous probability value (times 100 and between 0 and 100) is

$$p_{t+1} \;=\; f^P(d_t, j_t, \ell_t, h_t, D_t * b_t, D^S_{t+1}, B_{t+1}, X_t, W_t, Z^P_t, \mu^P, \nu^P_t) \tag{19}$$

5.3 Estimation Strategy

Having introduced the dynamic equations that capture individual testing behavior, I detail the estimation method in this subsection. The set of correlated equations also account for non-random attrition from the survey and initially-observed non-random behaviors and health outcomes when individuals first enter the data set. Next, I discuss the strategy for

estimating the correlation across equations as well as identification. Finally, I present the likelihood function that is estimated via full information maximum likelihood.

5.3.1 Attrition from the survey

Aside from death (which is modeled in the dynamic equations), individuals may attrit from the research sample. I allow potentially non-random attrition at the end of a period to depend on observed behaviors and updated health outcomes as well as the permanent and time-varying unobserved heterogeneity. Conditional on being alive in period t, the probability of attriting from the sample by the next period ($E^A_{t+1} = 1$), relative to the probability of being in the sample ($E^A_{t+1} = 0$) next period is:

$$ln[\frac{P(E^A_{t+1} = 1|E^A_t = 0)}{P(E^A_{t+1} = 0|E^A_t = 0)}] \;=\; f^{EA}(h_t, D_t * b_t, D^S_{t+1}, B_{t+1}, p_{t+1}, X_t, \mu^{EA}, \nu^{EA}_t) \qquad (20)$$

5.3.2 Initial conditions

The research sample includes individuals' behaviors and health outcomes beginning in year 2004. These initially-observed behaviors and outcomes cannot be explained using the dynamic specifications of equations 6-19 because I do not observe information prior to year 2004. Therefore, I specify static reduced-form equations to account for the non-random initial behaviors and health outcomes I observe in the data. Specifically, I model five initial conditions: (1) initial employment status (j_0); (2) initial blood sugar level (A_1); (3) initial revealed true disease state interacted with blood sugar test ($D_0 * b_0$); (4) initial subjective disease state (D^S_1); and (5) initial BMI (B_1). The initial condition equations are functions of exogenous individual characteristics in 2004 (X_0), relevant regional price and supply side variables in 2004 (Z_0, P_0), and permanent unobserved heterogeneity. The time-varying regional variables in year 2004 serve as exclusion restrictions because they are correlated with the initially-observed behaviors and health outcomes, but do not impact the subsequent behaviors (modeled dynamically) after conditioning on the endogenous behaviors and health outcomes.

5.3.3 Distribution of unobserved heterogeneity

The full set of 20 equations are correlated across time and across equations through the permanent unobserved heterogeneity. The time-varying unobserved heterogeneity captures additional correlation across equations within a time period and is not serially correlated. The initial condition equations are correlated with other initial equations

and the dynamic equations through the permanent unobserved heterogeneity. The correlations are achieved through a discrete factor random effect (DFRE) method, where the unobserved heterogeneity distributions are discretized and their mass points and associated weights are estimated jointly with other parameters of the likelihood function. The full information maximum likelihood method (FIML) is used to estimate the parameters. Specifically, I estimate the mass points of the joint distribution of permanent unobserved heterogeneity $\mu = [\mu^{DU}, \mu^{DD}, \mu^{J}, ...\mu^{E_i}, \mu^{EA}]$ and the probability weights, θ_m, $m = 1, 2, ..., M$, as well as the mass points of the joint distribution of time-varying unobserved heterogeneity $\nu_t = [\nu_t^{DU}, \nu_t^{DD}, \nu_t^{J}, ..., \nu_t^{ED}, \nu_t^{EA}]$ and the probability weights, ϕ_k, $k = 1, 2, ..., K$, jointly with other parameters. The number of total permanent (M) and time-varying (K) unobserved heterogeneity are determined empirically.

The DFRE method was initially suggested by Heckman and Singer (1984) in a single equation and extended to multiple equations by Mroz and Guilkey (1992) and Mroz (1999). This method minimizes possible estimation bias without imposing a stronger assumption about the distributions of the error components. In Monte Carlo simulations, the DFRE estimator shows reduced bias compared to the assumption of joint normality when the true distribution of unobserved heterogeneity is not jointly normal and the DFRE estimator performs as well as the assumption of joint normality when the true distribution of unobserved heterogeneity is jointly normal (Mroz, 1999).

Compared to a fixed effect method, the DFRE method has several advantages. First, I can estimate the individual permanent effect without estimating $N - 1$ additional parameters where N is the number of individuals in the sample. Second, I do not need to use differencing, which drops time-invariant explanatory variables from the analysis. Instead, I can estimate the marginal effects of the time-invariant variables on an individual's behaviors and outcomes. Additionally, I do not need to rely on the 'switchers' who have changes in those time-varying variables to identify their marginal effects on an individual's behaviors and outcomes.

5.3.4 Identification

Identification of the multiple equation dynamic model is achieved in three ways. First, theory and the timing of decisionmaking informs specification of the health outcome equations. For example, subjective health status depends on behaviors chosen in the period, and are independent of exogenous variables that shift those behaviors. Specifically, the $\boldsymbol{Z}$ variables and some state-level price variables $\boldsymbol{P}$ impact demand behaviors, but do not impact health outcomes conditional on the behaviors. Second, the entire history of the exogenous variables serve to identify behaviors over time. The initial conditions also

include exogenous time-varying variables that identify these equations. Lastly, functional form of the equations and a few covariance restrictions on the unobserved heterogeneity distributions help the identification.

Table 4 summarizes the $\boldsymbol{Z}$ variables and state-level price and supply side variables ($\boldsymbol{P}$) that capture supply side medical care conditions, demand side employment conditions, and exogenous health determinants. The state-level medical care related supply side factors include hospital beds per 1,000 population, number of total hospitals, total active physicians per 100,000 population, and health care cost index.[18] The first two variables are from the American Hospital Association (AHA) Annual Survey.[19] The state-level total active physicians per 100,000 population data are collected from the State Physician Workforce Data Book.[20] The state-level health care cost index is obtained from the ACCRA Cost of Living Index, which now is known as the Cost of Living Index (COLI) that measures living cost variation in different areas. The health care cost index measures the relative price levels for health care related consumer goods and services in a state relative to the average for all participating places (which equals 100). The state-level unemployment rate, which is obtained from the Bureau of Labor Statistics, reflects variation in demand for employment across states and over time.

The state-level health behavior related price variables and exogenous health determinants consist of the price index for fresh food, the prices of beer and wine, the price of cigarette, and annual average temperature and total precipitation. The price index for fresh food is calculated as the weighted average price of fresh food items using the ACCRA Cost of Living Index price data.[21] The prices of beer and wine are obtained directly from the ACCRA price data. The price of cigarette is obtained from Orzechowski and Walker (2014). The annual average temperature and total precipitation are obtained from the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental information. For all the price and supply side variables, two-year averages are calculated from the annual data.

[18]The state-level hospital beds per 1,000 population include staffed beds for community hospitals, which represent 85 percent of all hospitals. The state-level total hospitals are also community hospitals.

[19]The data are obtained from the Kaiser Family Foundation State Health Facts.

[20]This information is from the Center for Workforce Studies, Association of American Medical Colleges

[21]The fresh food items include steak, ground beef, sausage, tuna, whole gallon milk, dozen eggs, margarine, Parmesan, potatoes, bananas, lettuce, bread, orange juice, coffee, sugar, cereal, sweet peas, peaches, and cooking oil. I exclude some other food items such as fried chicken, coke, potato chips, and frozen meals.

Table 4: Summary statistics of exclusion restriction variables

Variable	Mean	S.D.	Min	Max
Z variables				
Same gender parent is alive	0.176	0.381	0.000	1.000
Age of alive same gender parent	80.971	7.649	45.000	108.000
Age of deceased same gender parent	72.595	15.188	12.000	110.000
Health insurance				
Medicare only	0.199	0.400	0.000	1.000
Medicaid or VA/CHAMPUS only	0.031	0.173	0.000	1.000
Multiple public plans	0.081	0.273	0.000	1.000
Medicare plus private plan	0.274	0.446	0.000	1.000
Medicaid/VA/Multiple public plus private plan	0.024	0.152	0.000	1.000
Employer-provided plan only	0.193	0.395	0.000	1.000
Spouse employer-provided or other private plans	0.114	0.318	0.000	1.000
Long-term care (LTC) only or uninsured	0.073	0.260	0.000	1.000
Health insurance missing	0.011	0.102	0.000	1.000
State level price/supply side factors (P)				
Hospital beds per 1,000 population	2.910	0.944	1.700	6.150
Total hospitals	97.155	79.098	6.000	427.000
Total active physicians per 100,000 population	258.630	99.623	171.600	880.600
Health care cost index	102.064	11.494	50.884	164.170
Unemployment rate	6.271	2.156	2.750	13.150
Annual average temperature (F)	52.915	8.998	25.650	78.600
Annual total precipitation (inches)	37.543	14.403	7.640	62.395
Price index for fresh food	2.321	0.240	1.960	3.499
Price of cigarettes ($)	4.216	0.949	2.864	8.017
Price of beer ($)	7.092	0.444	6.220	9.025
Price of wine ($)	6.065	0.775	4.272	8.677

Note: The summary statistics for Z variables are at person-wave observation level (which includes 77,881 person-wave observations) and the summary statistics for state level price variables are at state-wave level (which includes 255 state-wave observations).

5.3.5 Likelihood function

Unconditional on the unobserved heterogeneity the likelihood function is

$$
\begin{aligned}
L(\Theta) = \prod_{n=1}^{N} \Bigg\{ \sum_{m=1}^{M} \theta_m \Bigg[& \prod_{i=1}^{3} \prod_{q=0}^{Q^i} Pr(I^i = q|\mu_m^i)^{\mathbb{1}[I_n^i=q]} \prod_{i=4}^{5} f^{I^i}(I_n^i|\mu_m^i) \\
& \cdot \prod_{t=1}^{T_n} \Bigg[\sum_{k=1}^{K} \phi_k \prod_{r=0}^{3} Pr(dn_t = r|\mu_m^{DU}, \nu_{kt}^{DU}, D_{t-1} \leq 0)^{\mathbb{1}[dn_{nt}=r]} \\
& \quad \cdot \prod_{d=1}^{3} Pr(dd_t = d|\mu_m^{DD}, \nu_{kt}^{DD}, D_{t-1} > 0)^{\mathbb{1}[dd_{nt}=d]} \cdot \prod_{j=0}^{2} Pr(j_t = j|\mu_m^{J}, \nu_{kt}^{J})^{\mathbb{1}[j_{nt}=j]} \\
& \quad \cdot \prod_{\ell^1=0}^{3} Pr(\ell_t^1 = \ell^1|\mu_m^{L^1}, \nu_{kt}^{L^1})^{\mathbb{1}[\ell_{nt}^1=\ell^1]} \cdot \prod_{\ell^2=0}^{1} Pr(\ell_t^2 = l^2|\mu_m^{L^2}, \nu_{kt}^{L^2})^{\mathbb{1}[\ell_{nt}^2=\ell^2]} \\
& \quad \cdot \prod_{\ell^3=0}^{1} Pr(\ell_t^3 = \ell^3|\mu_m^{L^3}, \nu_{kt}^{L^3})^{\mathbb{1}[\ell_{nt}^3=\ell^3]} \cdot \prod_{b=0}^{1} Pr(b_t = b|\mu_m^{PB}, \nu_{kt}^{PB}, D_{t-1} \leq 0, dn_t \geq 2)^{\mathbb{1}[b_{nt}=b]} \\
& \quad \cdot Pr(h_{nt} = 0|\mu^H, \nu_{kt}^H)^{\mathbb{1}[h_{nt}=0]} \cdot Pr(h_{nt} > 0|\mu^H, \nu_{kt}^H)^{\mathbb{1}[h_{nt}>0]} \cdot f^H(h_{nt}|\mu_m^{H'}, \nu_{kt}^{H'}, h_{nt} > 0) \\
& \quad \cdot f^A(A_{n,t+1}|\mu_m^A, \nu_{kt}^A) \cdot f^B(B_{n,t+1}|\mu_m^B, \nu_{kt}^B) \cdot f^P(p_{n,t+1}|\mu_m^P, \nu_{kt}^P) \\
& \quad \cdot \prod_{s=0}^{4} Pr(D_{t+1}^S = s|\mu_m^S, \nu_{kt}^S)^{\mathbb{1}[D_{n,t+1}^S=s]} \cdot \prod_{w=0}^{1} Pr(E_{t+1}^D = w|\mu_m^{ED}, \nu_{kt}^{ED})^{\mathbb{1}[E_{n,t+1}^D=w]} \\
& \quad \cdot \prod_{g=0}^{1} Pr(E_{t+1}^A = g|\mu_m^{EA}, \nu_{kt}^{EA})^{\mathbb{1}[E_{n,t+1}^A=g]} \Bigg] \Bigg] \Bigg\}
\end{aligned}
$$

where θ_m is the probability of type m permanent unobserved heterogeneity and ϕ_k is the probability of type k time-varying unobserved heterogeneity. $Pr(\cdot)$ is the probability of a behavior or outcome if it is discrete and $f(\cdot)$ represents the density of a behavior or outcome when it is continuous.

6 Estimation Results

6.1 Data fit

One way to evaluate whether the model captures individuals' behaviors and health outcomes well is to compare the simulated values from the estimated data generating process to those observed in the data. Table 5 displays the summary statistics for the behavior and health outcome probabilities and values. Most behaviors and health outcomes fit the observed data very well. I assign the diagnosed stage of diabetes based on the simulated

A1c value and the empirical probabilities of transitioning to every stage of diabetes. I over-predict the probability of getting diagnosed with diabetes and the stage of diabetes with oral medication. This may be because I apply a more strict standard to diagnose diabetes compared to the one used by physicians.

Table 5: Summary Statistics of Data Fit

	Observed		Simulated	
Variable	Mean	S.D.	Mean	S.D.
Level of doctor visits				
None	0.069	0.254	0.068	0.251
Low	0.648	0.478	0.646	0.478
High	0.283	0.450	0.287	0.452
Employment				
No work	0.719	0.450	0.728	0.445
Part-time	0.051	0.220	0.050	0.218
Full-time	0.230	0.421	0.221	0.415
Lifestyle behavior				
Exercise				
None	0.240	0.427	0.243	0.429
Mild	0.213	0.409	0.221	0.415
Moderate	0.308	0.462	0.311	0.463
Vigorous	0.239	0.426	0.225	0.418
Smoking	0.130	0.336	0.131	0.338
Binge drinking	0.106	0.308	0.102	0.303
Stochastic outcomes				
Blood sugar test (if not diagnosed)	0.827	0.379	0.825	0.380
Probability of any hospitalization night	0.264	0.441	0.265	0.441
Number of hospitalization night (if any)	8.057	13.152	6.869	9.284
Health outcome				
A1c value (if not missing)	5.885	1.003	6.144	1.372
Diabetes state				
No test	0.139	0.346	0.137	0.343
Test and no diagnosis	0.636	0.481	0.604	0.489
Diagnosed without med treatment	0.034	0.182	0.038	0.191
Diagnosed with oral medication	0.136	0.343	0.160	0.367
Diagnosed with insulin shot	0.055	0.227	0.061	0.239
BMI value	28.374	6.026	28.409	6.029
Underweight	0.016	0.126	0.049	0.216
Normal	0.286	0.452	0.246	0.430
Overweight	0.367	0.482	0.306	0.461
Obese	0.331	0.471	0.399	0.490
Self-report health				
Excellent	0.100	0.300	0.084	0.277
Very good	0.305	0.460	0.297	0.457
Good	0.316	0.465	0.344	0.475
Fair	0.199	0.399	0.209	0.406
Poor	0.080	0.271	0.066	0.249
Two-year survival probability	85.491	22.225	84.911	21.206
Death	0.044	0.206	0.039	0.193

6.2 Estimation results

6.2.1 Determinants of doctor visits

Recall that there are two ways in which an undiagnosed individual can avoid a test: she may have a low level (or none) doctor visits and/or she may have a low probability of getting a test conditional on the level of doctor visits. I begin by looking at key contributors to doctor visit behavior (conditional on not being diagnosed with diabetes). In the next part, I turn to contributors to having a blood sugar test conditional on having a visit.

Table 6 reports the simulated contemporaneous marginal effects, which measure the one-period effects of the specified change on level of doctor visits while holding all other variables constant.[22] The simulations are based on estimation results from the FIML/D-FRE multiple equation model.[23] Tables with the complete estimation results for the level of doctor visits (i.e., Table A1) and other behaviors and outcomes are in Appendix F.

The simulated marginal effects provide evidence of the channels hypothesized in the theoretical and empirical framework. First, the monetary and time costs are essential determinants of doctor visits. Regarding time costs, a higher level of employment leads to fewer doctor visits. Specifically, for a full-time (part-time) worker, her probability of choosing a high level of doctor visits is 0.223 (0.229), this probability is 0.6 (3.2) percentage points (pp) higher if she is part-time (non-) employed for one period, holding all other variables constant. Likewise, the full-time (part-time) worker's probability of no visits decreases by 0.2 (0.3) pp if she is part-time (non-) employed. Monetary costs are measured by both household income and health insurance variables. Compared to an individual with a medium level of household income (i.e., $39,132), an individual with the 90th percentile of household income (i.e., $134,000) is more likely to have a high level of doctor visits by 0.3 pp and less likely to have none doctor visits by 0.7 pp. The doctor visits behavior is more sensitive to the price of doctor visits, which is measured by an individual's health insurance. Specifically, an individual with Medicare is 10.8 pp (85.0 percent) more likely to have a high level of doctor visits and 10.8 pp (or 56.5 percent) less likely to have none doctor visits than her counterparts with no health insurance. Second, longevity expectation also affects the doctor visit behavior. An individual who expects a higher probability of survival for another two years has slightly more doctor visits.

[22]The calculated marginal effects take into account all moments and interactions that involve the variable of interest.

[23]Because the data reveal that a small fraction of individuals with no visits during the period do report having their blood sugar tested, the dichotomous outcomes for no visits allow for this possibility in the estimation. The probability and percentage point changes in the "None" doctor visit category take into account both the dichotomous outcomes for no visits.

Lastly, we also find pessimism plays a significant role in explaining the level of doctor visits after modeling many other endogenous factors and the unobserved heterogeneity. Specifically, the marginal effects suggest that health anxious individuals are more likely to reduce the number of doctor visits (in order to avoid tests). On average, an individual with the least health anxiety (measured by the lowest pessimism value) are more likely to have a high level of visits by 3 pp (or 13.3 percent) and less likely to have no visits by 7.0 pp (or 51.1 percent) than those who are the most health anxious, holding other variables constant.

To figure out which barrier is more significant for the estimation sample, I also simulate the contemporaneous marginal effects of lifting each of the barriers for one period on the doctor visits behavior. That is, I take into account the share of the population who are currently suffering from each of barriers to evaluate the relative importance of each barrier. Those marginal effects are reported in the second half of Table 6. Compared to the baseline situation, the reduction of health insurance barrier has the largest effect on improving doctor visits. Giving everyone Medicare plus any private health insurance plan makes the population more likely to have a high level of doctor visits by 3.5 pp and less likely to have no visits by 3.2 pp. Reduction of health anxiety has the second largest effect. Specifically, reducing health anxiety to the lowest makes the population more likely to choose a high level of doctor visits by 0.6 pp and less likely to have no visits by 1.2 pp. This effect is even larger than increasing everyone's household income by one standard deviation (i.e., \$581,60.88).

Table 6: Simulations for the impacts of contributors to doctor visits
(conditional on not having been previousl diagnosed with diabetes)

Contemporaneous Marginal Effects	High		None	
Case 1 → Case 2	Case 1 (Level)	Case 2 - Case 1 (Δpp)	Case 1 (Level)	Case 2 - Case 1 (Δ pp)
Full time → Part time in t-1	0.223	0.6	0.082	−0.2
Part time → No work in t-1	0.229	3.2	0.081	−0.3
HH income medium → 90th percentile	0.250	0.3	0.077	−0.7
No insurance → Medicare	0.127	10.8	0.191	−10.8
Survival probability 50% → 100%	0.245	0.6	0.082	−0.4
Pessimism full effect (highest → lowest)	0.226	3.0	0.137	−7.0
Baseline	0.250		0.079	
→ No work		1.1		−0.1
→ HH income 1 S.D. higher		0.3		−0.7
→ Medicare+private plan		3.5		−3.2
→ Survival prob 100		0.2		−0.1
→ Pessimism lowest		0.6		−1.2
N	451,810			

Note: I control for all other variables in the estimation (Table A1 in Appendix F) and the simulations use estimation results from the FIML/DFRE multiple equation model.
Note 2: the medium household income is $39,132 and the 90th percentile household income is $134,000 S.D. of household income is $581,60.88.

6.2.2 Main contributors of blood sugar test

The previous equation captures determinants that explain an individual's doctor visit behavior. We now turn to understanding the key contributors to having a blood sugar test conditional on having a doctor visit. In other words, we measure the effect of the same determinants on the probability of not having a blood sugar test after conditioning on the level of doctor visits. The simulated contemporaneous effects for some key variables in the blood sugar testing equation are shown in Table 7. Direct effects are the effects of change in a specified variable on the probability of not having a blood sugar test conditional on having a doctor visit and not having been previously diagnosed with diabetes. Total effects measure both direct effects of the change in a specified variable on blood sugar tests as well as the indirect effects of that change on blood sugar tests through doctor visits and other health behaviors conditional on not having been diagnosed with diabetes.

The simulated marginal effects also support channels hypothesized in the theoretical and empirical framework. First, the time costs associated with taking a test plays a role. Compared to being full-time (part-time) employed, a non-employed individual is 0.5 pp (1.8 pp) or 3 percent (10 percent) less likely to not take a test, holding other variables constant. The total effect of time costs is slightly larger than direct effect after including the indirect effect from doctor visits and lifestyle behaviors. Second, the marginal effects

also indicate the importance of monetary costs associated taking a test, which is reflected by the impacts of both household income and health insurance (which captures the price of a test). Compared to an individual with a medium level of household income (i.e., \$39,132), an individual with a 90th percentile household income (i.e.,\$134,000) is less likely to not have a test by 0.5 pp. An individual with Medicare is 6.1 pp (or 26.9 percent) less likely to not have a test than an individual with no health insurance. The total effect of health insurance is much larger after considering its impact on doctor visits. Third, the life expectancy channel is also significant as individuals with higher subjective two-year survival probabilities are less likely to avoid the test. For example, the probability of no test for an individual who holds a 100% 2-year survival probability is 1.5 pp (or 8.6 percent) lower than an individual who holds a 50% survival probability.

Lastly, pessimism plays an important role even after we model the endogeneity of many important aspects of the problem as well as the unobserved heterogeneity. The results imply that health anxious individuals are more likely to avoid blood sugar tests conditional on the level of doctor visits (and many other factors). The measured direct marginal effect of pessimism indicates that the probability of no blood sugar test for a least health anxious individual (i.e., with the lowest pessimism value) is 3.8 pp (or 19.6 percent) lower than that of a most health anxious individual (i.e., with the highest pessimism value), while holding all other variables constant. The total effect of pessimism is slightly higher when considering its impact on doctor visits and lifestyle behaviors.

I also simulate the contemporaneous marginal effects of lifting each of the barriers for one period on blood sugar tests to evaluate their relative importance to current population. Both direct and total effects are reported in the second half of Table 7. The simulation suggests that the reduction of health anxiety to the lowest (measured by pessimism values) has the largest direct effect to make people less likely to avoid a test conditional on the level of doctor visits. It also has the second largest total effect to make people less likely to not have a test after considering its impact on doctor visits and lifestyle behaviors. This effect is larger than increasing everyone's household income by one standard deviation (i.e., \$581,60.88).

Table 7: Simulations for the impact of reductions in barriers on the probability of no blood sugar test (if undiagnosed)

Contemporaneous Marginal Effects	Direct Effects[a]		Total Effect[b]	
Case 1 → Case 2 (Reduction in Barrier)	Case 1 (Level)	Case 2 - Case 1 (Δpp)	Case 1 (Level)	Case 2 - Case 1 (Δpp)
Full time → No work	0.166	−0.5	0.178	−0.6
Part time → No work	0.180	−1.8	0.194	−2.2
HH income medium → 90th percentile	0.164	−0.5	0.175	−0.7
No insurance → Medicare	0.227	−6.1	0.282	−10.8
Survival probability 50% → 100%	0.175	−1.5	0.183	−1.1
Pessimism full effect (highest → lowest)	0.194	−3.8	0.207	−4.0
Baseline	0.164		0.175	
→ No work		−0.2		−0.3
→ HH income 1 S.D. higher		−0.5		−0.6
→ Medicare+private plan		−0.7		−1.9
→ Survival prob 100		−0.4		−0.3
→ pessimism lowest		−0.9		−0.9
N	417,410		451,810	

a: Direct effects are the effects of change in a specified variable on the probability of not having a blood sugar test conditional on having any doctor visits and not having been previously diagnosed with diabetes.
b: Total effects measure both direct effects of the change in a specified variable on blood sugar tests as well as the indirect effects of that change on doctor visits and other health behaviors.
Note 1: I control for all other variables in the estimation (Table A5 in Appendix F) and these simulations use results from the FIML/DFRE multiple equation model.
Note 2: the medium household income is $39,132 and the 90th percentile household income is $134,000. 1 S.D. of household income is $581,60.88.

6.2.3 Lifestyle behaviors

Entering a period, an individual may have been diagnosed with diabetes or not diagnosed. If diagnosed, she learns the true disease state and may be receiving different types of care based on the true disease state; this health information may influence the observed lifestyle behaviors. If not diagnosed, she may receive a blood sugar test (and the associated health information) or not in the previous period. Individuals with those different characteristics may choose different lifestyle behaviors. The contemporaneous marginal effects of the variables of interest in the lifestyle behavior equations (i.e., the levels of exercise, smoking, and binge drinking equations) are reported in Table 8.

Let's first look at whether an individual who takes a test and is not diagnosed with diabetes responds to the gained health information and adjusts her lifestyle behaviors. Compared to an individual who does not take a test in the last period, an individual who takes a test is less likely to not exercise or take a mild exercise by 1.6 pp (or 6.6 percent) and 0.4 pp (or 1.8 percent), respectively, but she is more likely to engage in vigorous exercise by 0.8 pp (or 3.4 percent). She is also more likely to smoke and binge drink by

5.0 and 0.5 pp, respectively.

If the individual is diagnosed with diabetes, she also adjusts her lifestyle behaviors according to the type of care she receives. The simulated marginal effects suggest that an individual who is diagnosed with diabetes are less likely to take any exercise and to engage in vigorous exercise than an individual without diabetes diagnosis or receives less severe treatment. For example, compared to an individual who takes a test and is not diagnosed with diabetes, an individual who is diagnosed with diabetes but has no medical treatment is more likely to not exercise by 1.4 pp and less likely to do vigorous exercise by 0.3 pp. While a diabetic individual with insulin treatment is more likely to not exercise by 5.8 pp and less likely to do vigorous exercise by 4.5 pp than a diabetic individual with oral medication treatment. The simulated marginal effects also suggest that individuals response to the diagnosis of diabetes by reducing smoking and binge drinking behaviors. Individuals with higher longevity expectations do more exercise, less likely to smoke, but more likely to binge drink. Lastly, individuals with higher body mass are more likely to have none or mild exercise and less likely to do vigorous exercise, but they are less likely to smoke or binge drink, holding other variables constant.

Table 8: Simulations for the impacts of health information on lifestyle behaviors

Contemporaneous Marginal Effects	Exercise: none		Exercise: mild		Exercise: vigorous	
Case 1 → Case 2	Case 1 (Level)	Case 2 - Case 1 (Δpp)	Case 1 (Level)	Case 2 - Case 1 (Δpp)	Case 1 (Level)	Case 2 - Case 1 (Δpp)
No test → Test and no diabetes	0.244	−1.6	0.218	−0.4	0.234	0.8
Test and no diabetes → Diabetes without med	0.228	1.4	0.215	−2.2	0.242	−0.3
Diabetes without med → Diabetes with med	0.242	0.5	0.193	4.0	0.239	−2.4
Diabetes with med → Diabetes with insulin	0.247	5.8	0.233	−1.5	0.215	−4.5
Survival probability 50% →100%	0.244	−1.0	0.220	−0.6	0.226	1.3
BMI: 20→32	0.210	7.0	0.185	5.5	0.273	−8.0

	Smoking		Binge drinking	
Case 1 - Case 2	Case 1 (Level)	Case 2 - Case 1 (Δpp)	Case 1 (Level)	Case 2 - Case 1 (Δpp)
No test → Test and no diabetes	0.085	5.0	0.106	0.5
Test and no diabetes → Diabetes without med	0.136	3.4	0.111	−2.5
Diabetes without med → Diabetes with med	0.170	−2.1	0.086	−0.7
Diabetes with med → Diabetes with insulin	0.149	−1.0	0.080	−0.9
Survival probability 50% →100%	0.141	−1.3	0.098	0.8
BMI: 20→32	0.172	−5.6	0.107	−1.2

Note 1: I control for all other variables in the estimation (Table A3 and A4 in Appendix F) and the simulates use estimation results from the FIML/DFRE multiple equation model.

6.2.4 Health production

Knowing that the underlying blood sugar evolution governs an individual's diabetes state transition and that body mass is highly correlated with the onset of diabetes and risks of other complications, I discuss the key determinants of those production processes.

Blood sugar evolution

An individual's blood sugar level (A1c value) depends on her BMI entering the period, her diabetes state in the period, and her medical and non-medical care inputs chosen in the current period. The simulated contemporaneous effects, both direct and total effects, of some key contributors to the A1c evolution are displayed in Table 9. The direct effects and total effects are very close, so I focus my discussion on the direct effects.

Several mechanisms of blood sugar evolution that are consistent with our hypotheses are discovered. First, diabetes state plays an important role in influencing an individual's blood sugar level: an individual who is diagnosed with diabetes has higher blood sugar levels (measured by the A1c test readings) than those without diabetes. For example, an individual with diabetes but no medical treatment has a higher A1c value by 0.487 units (or 8.2 percent) than an individual who is tested but not diagnosed with diabetes. In addition, among people with diabetes, the ones receive insulin shot or oral medication have higher blood sugar levels than those receiving no medical treatment. Second, doctor visits have protection effects on an individual's blood sugar level. Specifically, an individual with a high level of doctor visits has a lower A1c reading by 0.031 units (or 0.5 percent) than an individual with a low level of doctor visits. Third, body mass (BMI) influences blood sugar levels. On average, an individual with a BMI of 32 (i.e., who is obese) has a higher A1c reading by 0.172 units (2.9 percent) than an individual with a BMI of 20 (i.e., who has normal weight). Lastly, lifestyle behaviors also impact the evolution of blood sugar levels. A higher level of exercise makes the individual have a lower blood sugar level. If an individual starts to binge drink, her A1c value becomes 0.096 units lower. This result is consistent with some medical research that claims "while moderate amounts of alcohol may cause blood sugar to rise, excess alcohol can actually decrease your blood sugar level" (WebMD Medical, 2017).[24]

[24] `https://www.webmd.com/diabetes/guide/drinking-alcohol` access in October 2017

Table 9: Simulations for the impacts of key determinants on blood sugar evolution

Contemporaneous Marginal Effects	Direct Effects[a]			Total Effects[b]		
Case 1 → Case 2	Case 1 (Level)	Case 2- Case 1 ΔValue	Case 2- Case 1 ΔPercent	Case 1 (Level)	Case 2- Case 1 ΔValue	Case 2- Case 1 ΔPercent
Doctor visits: low → high	6.125	−0.031	−0.5	6.130	−0.034	−0.6
Exercise: none → mild	6.104	0.027	0.4	6.105	0.029	0.5
Exercise: mild → moderate	6.131	−0.005	−0.1	6.133	−0.005	−0.1
Exercise: moderate → vigorous	6.126	−0.028	−0.5	6.129	−0.028	−0.5
Smoke → No smoke	6.146	−0.036	−0.6	6.155	−0.043	−0.7
Binge drink → No binge drink	6.029	0.096	1.6	6.033	0.095	1.6
No test → Test and no diabetes	5.916	0.021	0.4	5.917	0.020	0.3
Test and no diabetes → Diabetes without med	5.936	0.487	8.2	5.937	0.488	8.2
Diabetes without med → diabetes with med	6.423	0.252	3.9	6.425	0.254	3.9
Diabetes with med → diabetes with insulin	6.675	0.527	7.9	6.678	0.521	7.8
BMI: 20 → 32	6.000	0.172	2.9	6.004	0.173	2.9

a: Direct effects are the effects of change in specified variable on the blood sugar level (or A1c reading).
b: Total effects measure both direct effects of the change in specified variable as well as the indirect effects of that change on blood sugar test, diagnosis of diabetes, and hospital nights.
Note: I control for all other variables in the estimation (Table A7 in Appendix F) and the simulations use estimation results from the FIML/DFRE multiple equation model.

BMI production

The BMI production depends on an individual's diabetes state and her medical and non-medical inputs in the current period. Additionally, since BMI production may reflect an individual's diet or nutrition behavior that we do not observe directly from data, the BMI production may also depend on the health information associated with a blood sugar test. The simulated direct and total marginal effects are shown in Table 10. The direct effects and total effects are very close, so I also focus my discussion on the direct effects.

First, lifestyle behaviors are significant predictors of BMI production. Generally, a higher level of exercise leads to lower BMI values. For example, compared to having a moderate level of exercise, having a vigorous level of exercise lowers an individual's BMI by 0.122 units (or 0.4 percent) and having a mild level of exercise elevates her BMI by 0.162 units, holding all other variables constant. On average, smoking reduces an individual's BMI by 0.418 units. This result is consistent with the finding that current smokers have significantly lower BMI than never smokers using the National Health and Nutrition Examination Surveys (NHANES) (Plurphanswat and Rodu, 2014).

Second, diabetes states are also important contributors to BMI production through medical treatment and information effects. Compared to an individual who is tested but not diagnosed with diabetes, an individual who is diagnosed with an early stage of diabetes (i.e., diabetes without medical treatment) has a lower BMI by 0.180 units (or 0.6 percent). The negative effects of the diagnosis of an early stage diabetes may reflect that

an individual responds to this health information and consumes a better diet to control her body mass. However, having oral medication or insulin shot as a treatment for diabetes increases an individual's BMI. This result is consistent with the studies showing that weight gain is not an uncommon phenomenon among people taking insulin treatments. The marginal effects also suggest that individuals are not likely to change diet behavior and respond to health information associated with a test but no diagnosis of diabetes. However, we do find them to respond to this health information by increasing exercise levels. Lastly, individuals with higher longevity expectations have lower body mass.

Table 10: Simulations for the impacts of key determinants on body mass production

Contemporaneous Marginal Effects	Direct Effects[a]			Total Effects[b]		
	Case 1	Case 2 - Case 1		Case 1	Case 2 - Case 1	
Case 1 → Case 2	(Level)	ΔValue	ΔPercent	(Level)	ΔValue	ΔPercent
Exercise: none → mild	28.439	0.064	0.2	28.449	0.072	0.3
Exercise: mild → moderate	28.503	−0.162	−0.6	28.521	−0.161	−0.6
Exercise: moderate → vigorous	28.341	−0.122	−0.4	28.361	−0.120	−0.4
Smoke → No smoke	28.006	0.418	1.5	28.032	0.407	1.5
Binge drink → No binge drink	28.393	−0.026	−0.1	28.414	−0.030	−0.1
No test → Test and no diabetes	28.355	0.002	0.0	28.368	−0.006	0.0
Test and no diabetes → Diabete without med	28.357	−0.180	−0.6	28.363	−0.183	−0.6
Diabetes without med → Diabetes with med	28.177	0.195	0.7	28.180	0.199	0.7
Diabetes with med → Diabetes with insulin	28.372	0.351	1.2	28.379	0.335	1.2
Survival prob 50% → 100%	28.402	−0.044	−0.2	28.418	−0.042	−0.1

a: Direct effects are the effects of change in the specified variable on the body mass index value.
b: Total effects measure both direct effects of change in the specified variable as well as the indirect effect of that change on body mass through testing behavior, diabetes diagnosis and states, and hospital nights.
Note: I control for all other variables in the estimation (Table A8 in Appendix F) and the simulation use estimation results from the FIML/DFRE multiple equation model.

7 Policy Simulations

With the estimated data generating process, I can simulate an individual's behaviors and health outcomes over time to evaluate some potential policy interventions. That is, I simulate the behaviors and outcomes of individuals assuming a policy is implemented and successfully changes some targeting behaviors of the individuals and then compare the simulated values to the ones for the baseline scenario (i.e., without the policy intervention). The policy simulations I discuss in this section include a wellness program that improves exercise behavior, a diabetes prevention program targeting at the exercise level of individuals with pre-diabetes, a national screening program for 60 years olds, and a health anxiety improvement program.

7.1 Simulation 1: A wellness program to improve exercise behavior

Given the importance of body mass and lifestyle behaviors to an individual's short- and long-term health outcomes, many health policies and programs are targeting at improving individuals' lifestyle behaviors. For example, the workplace wellness programs offer a group of activities to help the employees to have better lifestyle behaviors. According to the 2016 annual survey conducted by Kaiser Family Foundation (Kaiser) and the Health Research & Educational Trust (HRET), 46% of small firms and 83% of large firms offer a program in at least one of these areas: smoking cessation, weight management (e.g., on-site fitness programs or facilities), and behavioral or lifestyle coaching.

This policy simulation aims to evaluate the effects of a successful wellness program that establishes a high (i.e., vigorous) level of exercise among individuals. Specifically, it examines whether the high level of exercise can make the individuals (1) to have a higher rate of diabetes screening; (2) less likely to develop type-2 diabetes and pre-diabetes; and (3) to have fewer adverse health shocks and live longer. The policy simulation results are reported in Table 11.

The simulation results suggest that the wellness program improves individuals' health outcomes from several different aspects. First, it reduces the average body mass by 1.032 percent, which comes with the largest reduction in the share of obese observations, by 4.687 percent. Second, individuals are less likely to develop type-2 diabetes or pre-diabetes. The wellness program lowers the probability of new diabetes diagnosis by 1.360 percent, the probability of undiagnosed diabetes by 1.913 percent, and the probability of pre-diabetes by 1.537 percent. Third, individuals have lower medical care consumption, fewer adverse health outcomes, and live longer. Specifically, individuals are 10.181 percent less likely to have a high level of doctor visits, 12.226 percent less likely to have a night in hospital, and the average nights in hospital is 11.357 percent lower if any hospital night happens. The death rate is 10.181 percent lower.

However, the wellness program increases the probability of not having a blood sugar test over a two-years period by 1.425 percent, which leads to a slightly higher probability of unknown pre-diabetes in the population.

Table 11: Policy simulation: A wellness program to improve exercise level

Variable	Baseline Mean	Policy Simulation Mean	Percent change (%) Mean
Doctor visits			
None	0.068	0.070	3.232
Low	0.650	0.658	1.208
High	0.282	0.272	−3.561
Smoking	0.130	0.130	−0.064
Binge drinking	0.104	0.105	0.636
No blood sugar test (if no diagnosed)	0.173	0.176	1.425
BMI value	28.553	28.259	−1.032
Underweight	0.045	0.050	11.727
Normal	0.240	0.251	4.538
Overweight	0.309	0.312	0.955
Obese	0.407	0.388	−4.687
Prob of newly diagnosed diabetes (ind level)	0.106	0.104	−1.360
Prob of undiagnosed diabetes	0.081	0.079	−1.913
Prob of diagnosed diabetes	0.251	0.251	−0.020
Without med observations	0.037	0.037	−0.229
With oral medication	0.157	0.156	−0.245
With insulin shot	0.057	0.057	0.737
Prob of prediabetes	0.247	0.243	−1.537
Prob of unknown (among prediabetes)	0.172	0.175	1.603
Prob of having any hospital nights	0.258	0.227	−12.226
Number of hospital nights (if any)	6.764	5.996	−11.357
Death	0.037	0.033	−10.181
Total number of observations	535,887		
Total number of individuals	215,410		

7.2 Simulation 2: A diabetes prevention program

To prevent more people from developing diabetes, the CDC starts a lifestyle change program, which is designed for people who have prediabetes but have not developed diabetes yet, as part of the national diabetes prevention program. To be eligible for the CDC-recognize lifestyle change program, an individual has to be at least 18 years old, overweight (BMI $\geq$24, $\geq$22 if Asian), have no previous diagnosis of type 1 or type 2 diabetes, and have a blood test result in the pre-diabetes range (i.e., Hemoglobin A1C 5.7-6.4). Studies show that people with prediabetes who take part in the CDC's structured lifestyle change program can cut their risk of developing type 2 diabetes by 58 percent, and even 71 percent for people over 60 years old.

This policy simulation follows the CDC's lifestyle change program to impose a high level of exercise on people who is diagnosed with pre-diabetes, but with a more relaxed enrollment standard. That is, the program impose a high level of exercise on all individuals who have a blood sugar test and the result is in at least the pre-diabetes range (i.e., A1c $>$ 5.7), regardless of previous diagnoses of diabetes or BMI. The policy simulation results are displayed in Table 12.

The effects of the diabetes prevention program are very similar to the ones in the wellness program simulation, but with smaller magnitudes. Regarding improved health outcomes, the diabetes prevention program reduces average BMI value by 0.499 percent, which comes with a 2.335 percent reduction in the share of obese observations. With the diabetes prevention program, individuals are less likely to develop diabetes or pre-diabetes. Specifically, the probability of new diabetes diagnosis is 0.465 percent lower, the probability of undiagnosed diabetes is 0.814 percent lower, and the probability of developing pre-diabetes is 0.663 percent lower. Additionally, individuals have lower medical care consumptions, fewer adverse health shocks, and live longer. The probability of having a night in hospital, the average number of hospital nights (if any), and the death rate all reduce by around 6 percent, and individuals are 1.628 percent less likely to have a high level of doctor visits.

At the same time, the probability of not having a blood sugar test is slightly higher (by 0.451 percent), which causes the probability of a unknown pre-diabetes to be 0.501 percent higher.

Table 12: Policy simulation: A diabetes prevention program

	Baseline Mean	Policy Simulation Mean	Percent change (%) Mean
Doctor visits			
None	0.068	0.068	1.336
Low	0.650	0.654	0.567
High	0.282	0.277	−1.628
Exercise			
None	0.233	0.109	−53.072
Mild	0.223	0.114	−48.681
Moderate	0.314	0.167	−46.746
Vigorous	0.230	0.609	164.735
Smoking	0.130	0.130	−0.081
Binge drinking	0.104	0.105	0.222
No blood sugar test (if no diagnosed)	0.173	0.174	0.451
BMI value	28.553	28.411	−0.499
Underweight	0.045	0.047	4.640
Normal	0.240	0.245	2.199
Overweight	0.309	0.311	0.698
Obese	0.407	0.397	−2.335
Prob of newly diagnosed diabetes (ind level)	0.106	0.105	−0.465
Prob of undiagnosed diabetes	0.081	0.080	−0.814
Prob of diagnosed diabetes	0.251	0.251	0.276
Without med observations	0.037	0.037	0.153
With oral medication	0.157	0.157	0.079
With insulin shot	0.057	0.057	0.897
Prob of prediabetes	0.247	0.245	−0.663
Prob of unknown (among prediabetes)	0.172	0.173	0.501
Prob of having any hospital nights	0.258	0.241	−6.454
Number of hospital nights (if any)	6.764	6.327	−6.464
Death	0.037	0.034	−6.049
Total number of observations	535,887		
Total number of individuals	215,410		

7.3 Simulation 3: A national diabetes screening program at age 60

The lack of information about own health acts as a barrier to better lifestyle behaviors in the population. As a result, many countries have started to implement national screening programs to address the lack of information and promote better lifestyle behaviors. For example, the United Kingdom implemented a population-wide screening and prevention program for cardiovascular disease, the NHS Health Check program, in adults who are 40 to 74 years old in 2011 (Dalton and Soljak, 2012) and the National Health Screening Program (NHSP) in Korea provides various types of free health screenings since 1995 (Kim et al., 2017).

This policy simulation assumes a national diabetes screening program in the U.S. that provides diabetes screening for all individuals who are 60 years old and have not been diagnosed with diabetes. In this policy simulation, I am interested in whether this national diabetes screening program can improve individuals' diabetes screening behaviors afterward (i.e., after age 60) and their subsequent lifestyle behaviors and health outcomes. The simulation results are shown in Table 13. The sample I use for this policy simulation include all individuals who have not been diagnosed with diabetes at least till age 59.

According to the simulation results, this program improves individuals' overall screening behavior as well as the screening behavior after age 60. After implementing the policy, the probability of not having a blood sugar test in a 2-year period decreases by 22.890 percent overall and by 6.804 percent for people over 60 years old. Additionally, the national diabetes screening program helps individuals learn their true disease states, especially those with pre-diabetes. The simulation results suggest that it increases the rate of new diagnoses of diabetes by 8.431 percent but reduces the share of undiagnosed diabetic observations by 3.036 percent, it also reduces the probability of unknown pre-diabetes by 23.176 percent. Lastly, the national screening program also influences individuals' medical care consumption and lifestyle behaviors. With the program, the probability of no doctor visits is 4.478 percent lower but the probability of having any hospital nights is 1.436 percent higher. Individuals have slightly higher levels of exercise and lower BMI.

Table 13: Policy simulation: A national screening program at age 60

	Baseline Mean	Policy Simulation Mean	Percent change (%) Mean
Doctor visits			
None	0.087	0.083	−4.478
Low	0.701	0.702	0.160
High	0.212	0.215	1.314
Exercise			
None	0.157	0.157	−0.165
Mild	0.234	0.234	−0.132
Moderate	0.330	0.330	0.130
Vigorous	0.279	0.279	0.050
Smoking	0.164	0.168	1.988
Binge drinking	0.157	0.157	0.078
No blood sugar test (if not diagnosed)	0.191	0.147	−22.890
No blood sugar test (if no diagnosis and after age 60)	0.165	0.154	−6.804
BMI value	29.146	29.145	−0.004
Underweight	0.031	0.031	−0.611
Normal	0.212	0.212	0.051
Overweight	0.313	0.314	0.054
Obese	0.444	0.444	−0.020
Prob of newly diagnosed diabetes (ind level)	0.085	0.092	8.431
Prob of undiagnosed diabetes	0.091	0.088	−3.036
Prob of diagnosed diabetes	0.053	0.058	9.428
Without med observations	0.010	0.011	10.054
With oral medication	0.038	0.041	9.283
With insulin shot	0.005	0.006	9.275
Prob of pre-diabetes	0.298	0.297	−0.244
Prob of unknown (among prediabetes)	0.187	0.144	−23.176
Prob of having any hospital nights	0.181	0.184	1.436
Number of hospital nights (if any)	5.490	5.499	0.161
Death	0.007	0.007	1.502
Total number of observations	123,291		
Total number of individuals	40,444		

7.4 Simulation 4: Information campaign and awareness program target at information avoidance

There are many diabetes awareness programs and information campaigns. For example, the American Diabetes Association awareness program works to "reach communities throughout the United States to create awareness, prevent diabetes among at-risk populations, and ensure that all people with diabetes get the best care, treatment, and information about how to manage their diabetes". This policy simulation assumes an awareness program that alleviates health anxiety by providing information about diabetes prevention and educating individuals the importance of diabetes screening. In this policy simulation, I impose the lowest level of pessimism on all individuals. Although it is not very feasible to reduce the pessimism level of everyone to the lowest, this extreme case helps us to understand the largest effect of this type of policy. The policy simulation results are reported in Table 14.

The simulation results indicate, first, the program makes individuals less likely to avoid health information. The reduction of health anxiety reduces the probability of not having a blood sugar test (over a two-year period) by 5.502 percent, which leads to a 0.865 percent decrease in the probability of undiagnosed diabetic observations and a 5.243 percent decrease in the probability of unknown pre-diabetes. It causes a higher share of diagnosed diabetic observations, but more of them are in the early diabetes stages. Second, the program also makes individuals less likely to avoid doctor visits, reducing the probability of no doctor visits by 18.473 percent. Lastly, the reduction of health anxiety also influences individuals' lifestyle behaviors and makes them more likely to take a higher level of exercise and less likely to smoke.

Table 14: Policy simulation: A health anxiety improvement program

	Baseline Mean	Policy Simulation Mean	Percent change (%) Mean
Doctor visits			
None	0.068	0.055	−18.473
Low	0.650	0.657	1.007
High	0.282	0.288	2.101
Exercise			
None	0.233	0.211	−9.693
Mild	0.223	0.216	−3.074
Moderate	0.314	0.326	3.740
Vigorous	0.230	0.248	7.690
Smoking	0.130	0.114	−12.057
Binge drinking	0.104	0.108	3.650
No blood sugar test (if not diagnosed)	0.173	0.164	−5.502
BMI value	28.553	28.553	−0.002
Underweight	0.045	0.045	0.073
Normal	0.240	0.240	−0.023
Overweight	0.309	0.309	0.006
Obese	0.407	0.407	0.001
Prob of newly diagnosed diabetes (ind level)	0.106	0.107	0.983
Prob of undiagnosed diabetes	0.081	0.080	−0.865
Prob of diagnosed diabetes	0.251	0.252	0.519
Without med observations	0.037	0.037	0.599
With oral medication	0.157	0.158	0.555
With insulin shot	0.057	0.057	0.368
Prob of prediabetes	0.247	0.246	−0.209
Prob of unknown (among prediabetes)	0.172	0.163	−5.243
Prob of having any hospital nights	0.258	0.258	−0.017
Number of hospital nights (if any)	6.764	6.757	−0.117
Death	0.037	0.035	−3.464
Total number of observations	535,887		
Total number of individuals	215,410		

8 Conclusion

This paper evaluates the role of many contributors, including health anxiety, to the observed type-2 diabetes screening behavior by jointly estimating a set of equations derived from a forward-looking individual's decisionmaking optimization problem. With data from the HRS, I find that the monetary costs, time costs, health and longevity expectations, and health anxiety are all important contributors to an individual's blood sugar testing behavior. Specifically, a health anxious individual is less likely to receive a diabetes screening test by reducing the number of doctor visits and avoiding the test during a visit. Individual's health-related behaviors also respond to health information associated with screening tests.

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